Thesis for the degree of Philosophiae Doctor

Attribution of emissions and temperature change to producing and consuming regions and sectors

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Oslo, August 2014

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List of papers

Paper 1: Karstensen, J., Peters, G. P. & Andrew, R. M. 2013. Attribution of CO2 emissions from Brazilian deforestation to consumers between 1990 and 2010. *Environmental Research Letters*, 8, 024005.

Paper 2: Lenzen, M., Schaeffer, R., **Karstensen, J.** & Peters, G. P. 2013. Drivers of change in Brazil's carbon dioxide emissions. *Climatic Change*, 121, 815-824.

Paper 3: Karstensen, J., Peters, G. P. & Andrew, R. M. 2014. The temperature response to the current consumption of goods and services. *Climatic change (in review).*

Paper 4: Karstensen, J., Peters, G. P. & Andrew, R. M. 2014. Uncertainty in temperature response of current consumption-based emissions estimates. *Earth System Dynamics (in review).*

Contents

1. Introduction

The Working Group I of The Intergovernmental Panel on Climate Change (IPCC) recently released its Fifth Assessment Report, stating that "Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia" (Stocker et al., 2013). Furthermore, it says that "Continued emissions of greenhouse gases will cause further warming and changes in all components of the climate system". These changes are likely to have negative impacts on natural and human systems (IPCC, 2014e), and to avoid the worst effects, countries have to significantly reduce emissions over the next decades (IPCC, 2014d, Hoekstra and Wiedmann, 2014).

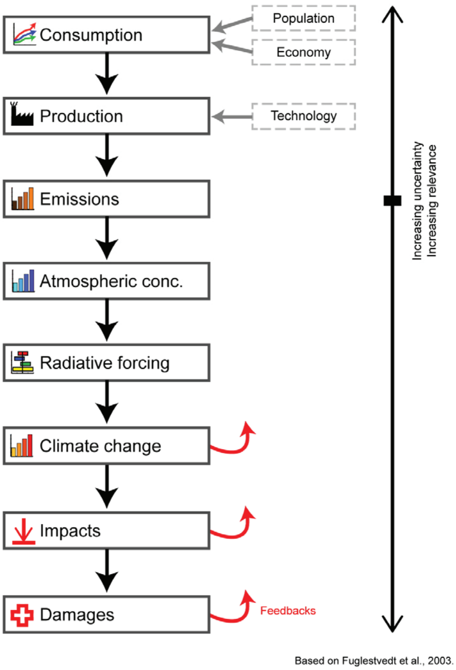

Figure 1: Simplified causal chain, connecting consumption and production with emissions and climate change. Based on Figure 1 from (Fuglestvedt et al., 2003).

In response to this challenge, climate negotiations have continued since the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 (UNFCCC, 1992). However, few countries have committed to significant reductions of emissions due to a combination of factors, such as economic interests, emission allocation disagreements (the principle of "common but differentiated responsibilities", stated in UNFCCC, can be interpreted in many ways), and uncertainties surrounding climate change and its impacts (Barrett and Dannenberg, 2012). Thus, international cooperation and binding agreements have been difficult to achieve, resulting recently in more than 3%/year increase of emissions on the global level and serious carbon leakage on the national level (Peters et al., 2012b).

Many argue that much of the historic responsibility of emissions lies with developed nations, as they were the first emitters (Höhne and Blok, 2005). Under the Kyoto Protocol, which was signed in 1997, many developed countries (Annex B countries) signed binding obligations to reduce emissions (UNFCCC, 1997). Although reductions were seen during the first commitment period from 2008 to 2012 (Peters et al., 2012b), recent studies have shown that these reductions are offset by the increasing trade with countries without binding targets (Peters et al., 2011c).

Today, the world is no longer clearly split between low-emitting developing nations and high-emitting developed nations, as 54% of the greenhouse gas (GHG) emissions in 2007 came from non-Annex B countries (European Commission, 2011). Although production has been shifted from developed to developing nations, a large share is still being exported back to developed nations (Peters et al., 2011c). This indicates that if only a selection of countries is going to have binding obligations, then the inclusion of trade in climate policy is long overdue.

Historic emissions have been responsible for most of the of the observed global warming of approximately 0.85°C, since pre-industrial times (IPCC, 2013). If the world follows a medium-to-high emission scenario, however, most of the temperature change that will happen due to anthropogenic emissions is yet to come (Peters et al., 2013, Stocker et al., 2013). Additionally, carbon emissions have never been as high as presently, thus the anthropogenic emissions' impact on the global climate system is at its largest (Peters et al., 2012b). Furthermore, the global carbon emission growth rate has exceeded 3%/year from 2000 to 2012 (Le Quéré et al., 2014), while, perhaps paradoxically, the level of scientific understanding of climate change recently has expanded dramatically (although large knowledge gaps still exists; (Stocker et al., 2013)). Thus, there is a need for addressing the *present* production and consumption that is driving current emissions and future climate change.

The connection between human behavior, i.e. socio-economic drivers, and climate change can be explained by a causal chain starting with human actions and ending in climate change impacts (Figure 1). Many underlying and overlapping drivers of emissions and climate change have been recognized (although they may represent correlation rather than direct causation, they can be associated with changes): such as population growth, economic growth, energy and GHG intensity, international trade and consumption, etc. (see IPCC (2014a) for an overview). This work focuses on the consumption of goods and services, which can be seen as a driver of production, as high demands for products can sustain or increase production. Production will usually lead to emissions, which may lead to climate change such as temperature and precipitation change. These effects may have impacts, such as sea-level rise and drought, which might lead to damages and economic loss.

This extended cause-effect chain suggests that consumption is considered as a driver. In fact, it can be argued that regional and sectoral consumption-based emissions is a complementary way of allocating emissions, as this compensates for the increasing geographic distance between production and consumption, which is made possible by international trade. In the consumption view, each country is allocated emissions occurring within the borders, as well as subtracting emissions embodied in exports and adding emissions from imports. The consumption approach therefore captures carbon leakage via imports, and thus may be a more policy-relevant measure of a country's emissions footprint. The consumption of goods and services can therefore be seen as one of the underlying drivers of emissions, which connects human behavior with climate change (Figure 2).

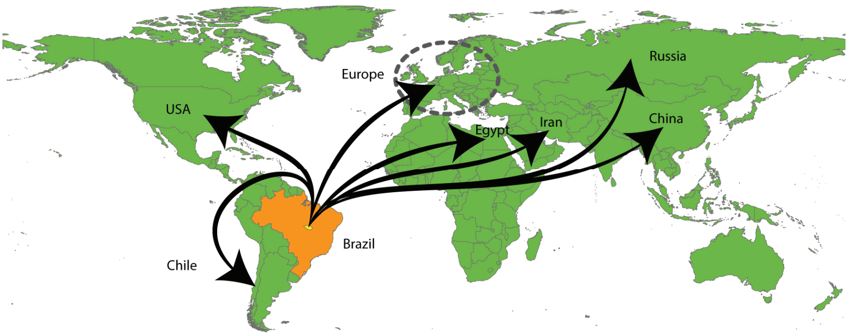

Figure 2: Major Brazilian export routes of meat and soy beans in 2007, which is driving production and thus causing deforestation and emissions in the Amazon.

The motivation behind this study is to extend the cause-effect chain to include consumption and temperature change. This study has been divided into focused work packages, which has resulted in four articles. Two of the articles have a special focus on Brazil, which is of global importance for several reasons: it has historically been, and still is, one of the world's largest emitters of greenhouse gases (especially due to deforestation), it is one of the world's largest economies, and it is one of the most important transition economies. The other two studies take a global focus, though results are presented for each country. In order to extend the studies on Brazilian emissions and trade for all sectors and pollutants, the Brazilian specific results from the global studies are extracted and discussed in section 4. This section additionally discusses the uncertainties in the Brazilian emissions, including LUC, and puts the results into a policy relevant context.

This thesis is supported by The Research Council of Norway, being a part of the project: *"Quantifying the global socio-economic and policy drivers for Brazil's contribution to global warming"*.

1.1. Objectives

The objectives of this study are to connect consumption with production, to estimate the regional and sectoral emissions through consumption, and to contrast the results with the established territorial perspective used in the Kyoto Protocol. Multiple pollutants are taken into account, and emissions are converted to global temperature change using an emission metric. Additionally, uncertainties of emission statistics, metric parameters and economic data are investigated to estimate the uncertainties of the individual components and the final results. A major focus is therefore to integrate datasets and models across disciplines in order to quantify and link the cause-effect chain. This kind of integrated assessment targets scientific breadth and how to make the different scientific disciplines come together to answer policy-relevant questions.

The general hypothesis is that: *consumption leads to climate change by driving production and emissions,* which is linked to the general question this study tries to answer:

> *What are the regional and sectoral producers and consumers of emissions and temperature change?*

This has been split up into articles with more precisely defined questions:

1. *What are the consuming regions and sectors of* CO_2 *emissions embodied in products from Brazilian deforestation?*
2. *What are the historical drivers of Brazils* CO_2 *emissions?*
3. *What are the current regional and sectoral producers and consumers of global temperature change?*
4. *How uncertain are consumption-based emissions and the corresponding temperature change?*

The Background section explores the motivation and concepts behind the studies, before the Data and modelling section briefly shows what background datasets and methods the analysis is building on. The final section, Conclusions and outlook, summarizes the main findings and discuss the potential implications of the results.

2. Background

This section discusses background theories and concepts, in order to understand the motivation, models and datasets used in the thesis. This section shows the state-of-the-art knowledge, and how this study builds on this to expand the understanding of the cause-effect chain. To estimate the climate effects of consumption, this research quantifies the steps of the casual chain leading from consumption to climate change. Emissions of several pollutants have been investigated, in what sectors and regions they are emitted and the temperature effect they have on the climate system. Furthermore, several accounting systems are discussed, and how emissions can be linked to trade. Lastly, an overview of the case of Brazil is presented. I start out by explaining the rational for investigating these topics.

2.1. Climate change

The Earth's climate system is governed by multiple processes, and is powered by incoming solar radiation (Figure 3). This system has historically nearly been in balance with outgoing radiation as the surface temperature has been relatively constant over centuries (Stocker et al., 2013). Approximately 30% of the incoming radiation is reflected back to space from the surface and atmosphere, due to reflective characteristics of some gases and aerosols, and by clouds and reflective surfaces. About 20% is absorbed by other compounds such as water vapor, aerosols and ozone, warming the atmosphere. The rest (about 50%) is absorbed by the surface.

The outgoing radiation from the surface to space is largely absorbed by greenhouse gases (GHGs; such as water vapor, CO_2, and CH_4), ozone and clouds in the atmosphere. These components re-emit radiation in all directions, heating the lower levels of the atmosphere and surface, and sending energy out to space. This greenhouse effect is increased with increasing concentrations of GHGs, trapping more heat in the lower levels of the atmosphere. Such a change creates an imbalance of the global energy budget (more incoming than outgoing energy), which will not reach equilibrium until the surface and atmosphere heats to a new level.

Observations have shown historical temperature changes in the last 1300 years, where there has been significantly temperature increases since the industrial revolution after

1850 (IPCC, 2007b). It is now believed that this increase, due to uptake of energy by the climate system because of GHGs, is a result of mainly human activities (IPCC, 2013). IPCC concluded that the period 1983-2012 was likely the warmest 30-year period of the last 1400 years, and the total global surface temperature increase from 1880 to 2012 has been estimated to 0.85°C (IPCC, 2013).

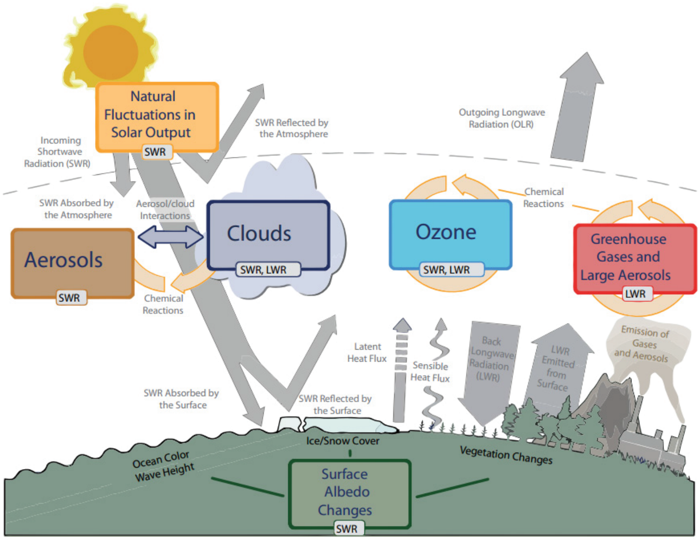

Figure 3: Earth's radiation balance. Figure from Stocker et al. (2013).

This temperature increase is due to a mix of warming and cooling compounds having complex effects in the atmosphere over different scales and time horizons. CO_2 emissions from fossil fuels and land-use change are believed to be one of the main causes of climate change, being responsible for about 75% of the emissions in 2010 (IPCC, 2014a). Global fossil and cement emissions grew with 1%/yr in the 1990s and 3.1%/yr from 2000-2012 (Le Quéré et al., 2014). Although the recent global financial crisis created a drop in emissions of 1.4% in 2009, the next year more than offset the decrease by increasing 5.9% and reaching a record of 9.1Pg C (Peters et al., 2012b). The emissions are mainly associated with human activities which require combustion of fossil fuels such as oil, gas or coal, which originate from economic sectors such as energy-intensive manufacturing, power generation and transport (Houghton, 2007). Emissions from forestry and land-use change (LUC) have been roughly stable over the last decades, but have become less dominating due to increasing fossil fuel emissions, being responsible for approximately 12% of global CO_2 emissions between 2002 and 2011 (Le Quéré et al., 2012). However, the estimates for LUC emissions are uncertain (Houghton et al., 2012).

Other important well-mixed GHGs (WMGHGs) include CH_4 and N_2O. Large emissions from these pollutants come from agriculture and manufacturing sectors (European Commission, 2011). Additionally, CH_4 has large emissions associated with the transportation and production of fossil fuels (Kirschke et al., 2013). Furthermore, aerosols and ozone precursors (short-lived climate forcers; SLCFs) also induce a radiative forcing on the climate system, leading to temperature change (Myhre et al., 2013a). These pollutants usually have shorter lifetimes and are not well-mixed, and can have a warming or cooling effect. Sulfur aerosols have large cooling effects, and is the largest anthropogenic source of aerosols, coming mainly from power generation, various industries and transportation (Smith et al., 2010, European Commission, 2011).

2.1.1. Emission metric

Multi-pollutant analysis and policy often requires comparing the effects of the pollutants on climate, which means they have to be put on the same scale by using an emission metric (Figure 4). However, the pollutants have different characteristics (i.e. radiative forcing, lifetime, atmospheric interactions), making a direct comparison of their effects less than straightforward (Fuglestvedt et al., 2003). This is because different policy questions may try to answer different questions, thus weighting metric choices differently (Fuglestvedt et al., 2010). These choices may include the unit of the effect (e.g. concentrations, radiative forcing, climate change, impacts or damages), at what time in the future the effect is modelled (e.g. 20 or 100 years) and which emissions that are considered. These are not only scientific choices, but also values-based choices, and might have a large impact on the results (Aamaas et al., 2013b).

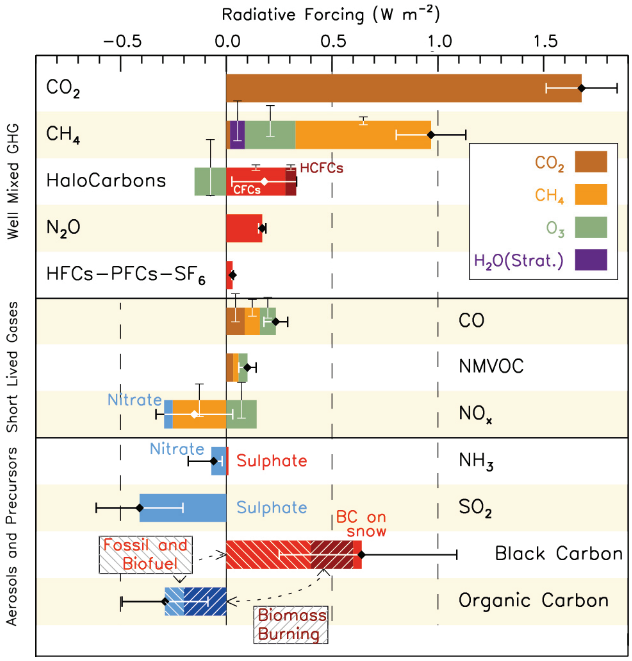

Figure 4: Pollutants affecting climate. Modified figure from Stocker et al. (2013).

The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC) uses the Global Warming Potential (GWP) when comparing and weighting the effects of WMGHGs with SLCFs. It was initially used in IPCC's first assessment report (FAR) in 1990 "to illustrate the difficulties inherent in the concept…", but has later been revised and used in all of IPCC reports due to its relatively simple definition and small number of required input parameters (IPCC, 1990). Consequently, emission targets in later years have been set using GWP, which is comparing pollutants through integration of their radiative forcing effect due to a pulse emission to a specific time horizon, which is normalized by the values of CO_2 (Fuglestvedt et al., 2003). Despite its name, GWP does not link directly to the climate response or temperature change, as different gases with similar RF values may have different temporal temperature impacts due to e.g. different lifetimes (Shine, 2009). Thus, the GWP has been critiqued by many authors for being adopted inadvertently as scientific consensus, when actually the metric and its parameters are mainly based on the policy context (Fuglestvedt et al., 2010, Manne and Richels, 2001, Tol et al., 2012).

The Kyoto Protocol uses the GWP with a 100 year time horizon, although it has been suggested that this was an arbitrary choice (Shine, 2009). Metric choices should be policy relevant, and since the time horizon has a large impact on the results, choosing one over another should ideally be justified. The long-term goal of the UNFCCC is to avoid dangerous climate change (Article 2), although debates in the scientific community have suggested that this threshold is difficult to define (IPCC, 2007a). More recently, the 2°C target has become a symbolic threshold, and governments have agreed that emissions should be reduced in order to avoid exceeding this target (den Elzen and Meinshausen, 2006, Rogelj et al., 2009, Major Economies Forum on Energy and Climate, 2009, UNFCCC, 2011a, UNFCCC, 2011b).

Since the GWP is not a measure of temperature change, it may not be a suitable tool for mitigation policies trying to avoid a specific global warming (Manne and Richels, 2001). The Global Temperature Change Potential (GTP) was developed in light of this, which includes the climate response to a change in radiative forcing (Shine, 2009). The metric models the global temperature effect at a chosen time horizon due to a pulse emission (Fuglestvedt et al., 2010), which also adds additional layers of uncertainty, as the climate sensitivity includes the atmospheric, land-based and ocean response and feedbacks to increased radiative forcing (Olivié and Peters, 2013). The GWP has a larger "memory" of SLCFs over time through integration of their effects to the chosen time horizon, thus SLCFs will have an effect on the metric values long after their temperature effects have declined. The GTP, on the other hand, is an end-point metric, where the memory is much less pronounced, thus SLCFs' effect decays with their temperature effect (Fuglestvedt et al., 2010).

The literature suggests that, by 2100, the global surface temperature is likely to exceed 1.5°C relative to the average between 1850 and 1900 for all scenarios except the very low-end (RCP2.6) (IPCC, 2013). However, new studies have found that a temperature increase of 2°C might happen much sooner, as the global emissions trend is following the high-end trend of possible scenarios (Peters et al., 2013). Estimates suggest that, given that emissions are continuing to increase at the current level, the 2°C degree threshold will be reached before or around 2060 (Joshi et al., 2011, Peters et al., 2013). Because the work in this thesis is made to be relevant for climate policy that is aimed at preventing dangerous climate change, and to be comparable with other recent studies (Aamaas et al., 2013a, Peters et al., 2011a, Borken-Kleefeld et al., 2013), this work mainly uses GTP with 50 year time horizon (Figure 5). Although recent studies have developed and evaluated temperature change potentials on a regional scale (Regional Temperature Potential) (Shindell, 2012, Collins et al., 2013), this study focus on the contributions to global temperature change when using the GTP.

The GTP50 metric, in contrast to the GWP100 metric, places less weight on the short-lived pollutants such as CH_4, BC, OC, SO_2 (Aamaas et al., 2013a). Economic sectors with high emissions of SLCFs, such as agriculture, transport and electricity generation therefore are given lower CO_2-eq. emissions (Figure 5 shows in what sectors emissions occur and are consumed). If a GTP100 was used, the differences would be larger, although the differences between GTP50 and GTP100 are relatively small for global emissions and the top regional emitters (Aamaas et al., 2013a). To illustrate the differences between time horizons, Paper 3 and 4 show continuous graphs of temperature impacts and uncertainties for all time horizons from 1 to 100 years.

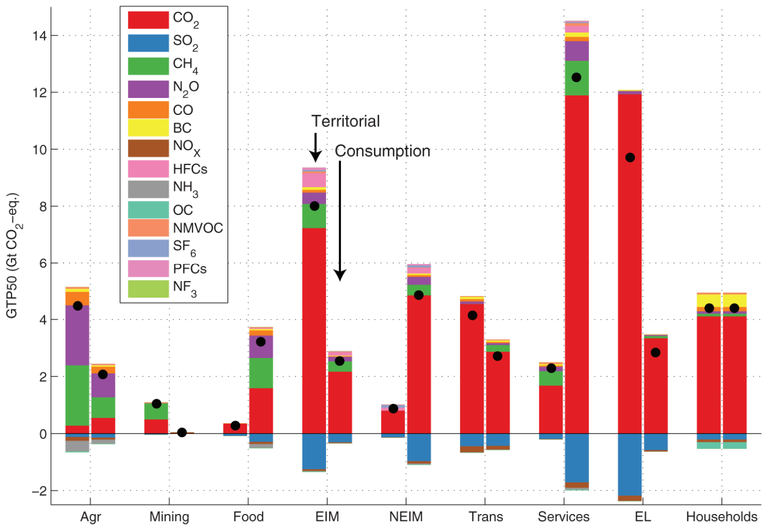

Figure 5: Global emissions occurring in economic sectors in 2007, using GTP50. Territorial emissions indicate in what sector emisisons are occuring, while consumption-based emissions show what sector emissions embodied in products are being purchased (see next section for details). Sector abbrivations: Agr – Agriculture, EIM – Energy intensive manufacturing, NEIM – Non-energy intensive manufacturing, Trans – Transport, EL – Electricity.

Despite efforts of emissions reductions, current global carbon emissions are higher than ever (Peters et al., 2012b), and the 2°C window is closing faster than previous believed (Peters et al., 2013, Le Quere et al., 2014). This study focuses on the current emissions leading to temperature change. By studying the future temperature effects of current emissions, it may be possible to create effective mitigation policies targeting large contributions which may also be relatively cheap to mitigate and include rapid co-benefits (Canadell and Raupach, 2008, IPCC, 2014a, Shindell et al., 2012).

2.2. Allocations of emissions (accounting systems)

The increasing risk of dangerous climate change made the international community come together and discuss emission reductions through the UNFCCC treaty in 1992 (UNFCCC, 1992). Climate negotiations, such as the Conference of the Parties (COP) meetings, occur every year and aim at forming legally binding agreements on mitigation and adaptation. In an effort to measure countries emission inventories and progress towards individual emissions reduction goals, the participating countries are required to submit annual national emission inventories (NEI) of the pollutants by sector (Peters, 2008). These emissions include "greenhouse gas emissions and removals taking place within national (including administered) territories and offshore areas over which the country has jurisdiction" (IPCC, 1996).

National climate policies and mitigation strategies therefore focus on domestic emissions, as this is the boundary for the inventories. This system is therefore taking a "producer" perspective on emission inventories, where the responsibility lies with the emitting sector and region (Eder and Narodoslawsky, 1999). Due to the difficulties of allocating responsibility and possible large changes in outcome with different techniques, the climate negotiations has become an arena for debates about how to share the burden of emissions among countries (den Elzen et al., 2005a, den Elzen and Schaeffer, 2002, Höhne et al., 2008), and how that is used to determine emission caps and reductions (den Elzen and Meinshausen, 2006). One of the most discussed methodologies was the Brazilian proposal, which was introduced just before the UNFCCC Kyoto COP meeting in 1997. Although it was not adopted, it presented a framework for allocating emissions responsibility based on contributions to historical global warming amongst industrialized nations (La Rovere et al., 2002). This too has received criticism, such as the complexity of the calculations and need for climate models, the need for reliable GHG data for individual countries, and the need for policy choices (La Rovere et al., 2002, den Elzen et al., 2005b). However, the idea of national responsibility of global temperature change due to GHG emissions has sparked numerous discussions in the science community (Höhne and Blok, 2005, den Elzen et al., 1999, Höhne and Harnisch, 2002, den Elzen et al., 2005b).

The first commitment period (2008-2012) of the Kyoto Protocol was largely a success, in the sense that the parties, together, exceeded their emission reduction target (IPCC, 2014c). The original Brazilian proposal included three of the most important GHGs; CO_2, CH_4 and N_2O, while the Kyoto Protocol additionally included HFCs, PFCs and SF_6 (den Elzen and Schaeffer, 2002). However, the climate policy does not cover non-Annex B countries, where most of the latest emission increase has occurred (Peters et al., 2012b). The second commitment period (2013-2020) is currently in effect, where most participating countries aim for a 20% reduction in emissions compared to their based year (UNFCCC, 2012). However, the climate policy covers less than 15% of global CO_2 emissions (Le Quéré et al., 2014), thus the emission reductions in the Kyoto Protocol will not be sufficient to avoid a 2°C global warming (IPCC, 2014c, UNEP, 2013). Three of the largest emitters (China, USA, India), who emitted more than 40% of global emissions in 2011 and are thought to be responsible for most future emissions, have not committed to emission reductions through the Kyoto Protocol (Ward and Mahowald, 2014, CAIT, 2014, UNFCCC, 1997).

This illustrates a major drawback with any emission accounting system which only deals with a selection of countries in a world, particularly where international trade is a substantial increasing part of global GDP (The World Bank, 2014). Recent studies have shown that international trade between developed and developing countries have offset emission reductions (Peters et al., 2011c), which todays accounting systems does not compensate for, and the trend continues to increase. This has lead to the term carbon leakage, which occurs when e.g. non-Annex B countries increase production in order to meet consumption demands in Annex B countries (Peters and Hertwich, 2008a, Paltsev, 2001). The emissions occurring to produce products for Annex B countries are not allocated to the Annex B counties under normal accounting rules. The reason for increased production abroad may be due to economic incentives (generally called weak carbon leakage), or be purely due to strict climate policy domestically (strong carbon leakage) (Peters, 2010b). Generally, Annex B countries have seen quite stable territorial emissions over the last decades, while non-Annex B nations have seen a rapid increase in territorial emissions, correlating with increasing international trade (Peters et al., 2012b).

To cover the carbon leakage, several global accounting systems for current emissions have been proposed. Along the global supply-chain, they can usually be grouped into one of three perspectives: (1) extraction, (2) production or (3) consumption (Davis and Caldeira, 2010). Extraction based emissions allocations focuses on where e.g. fossil fuels are extracted from the ground, i.e. the source of emissions, before being processed or refined (Davis et al., 2011). This view has not gained much attention, but illustrates the responsibility of extracting fossil fuels (Andrew et al., 2013).

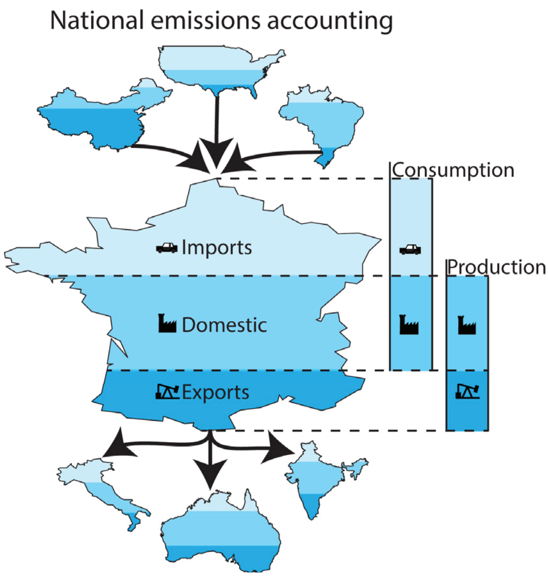

Figure 6: Imported, domestic, and exported products indicating production and consumption perspective.

In the production (territorial) perspective, emissions are allocated to where they are combusted, which is currently used under the Kyoto Protocol. Thus producers of exported goods and services are held responsible for the emissions occurred from the production (Figure 6). This perspective therefore allocates emissions embodied in trade to the producers, which in 2007 accounted for 24% of global CO_2 emissions (Andrew et al., 2013).

Using the consumption perspective, emissions are allocated to products in the global supply-chain to end users (consumers) (Hertwich and Peters, 2009, Davis and Caldeira, 2010, Davis et al., 2011). These purchases can usually be divided into final demand made by either households, governments or go to investments or exports (Peters, 2008). For a given country, the exports are allocated to the countries that purchase and consume the traded goods, while the imports are allocated to domestic emissions. The emissions included (embodied) in a product, includes all pollutants emitted in the production from raw material extraction to manufacturing and final sale (Peters and Hertwich, 2008b). This may be a "fairer" way of allocating emissions, as consumers are held responsible for sustaining and increasing production and emissions leading to climate change (Grasso and Roberts, 2014, Steininger et al., 2014).

This accounting system includes carbon leakage on imports, as the increasing production and trade between developing and developed nations is taken into account. Even if only a limited number of countries is included in a consumption-based climate policy, this approach would capture more of the global carbon leakage than the corresponding production perspective, as 60-70% of current global exports are destined for developed countries (Peters and Hertwich, 2008b). Figure 7 indicate that developed countries have had relatively stable emissions over time, and increasing emissions embodied in imports, while developing nations have increased emission footprints and emissions embodied in exports.

The consumption approach is based on emission allocations through the global supply-chain, which use economic trade data on a regional and sectoral level. This adds additional calculations and uncertainties compared to production approach as additional data is necessary. The next section discuss the methods of how to link emissions to trade, while the section after that takes a brief look at why Brazil is important in a global context.

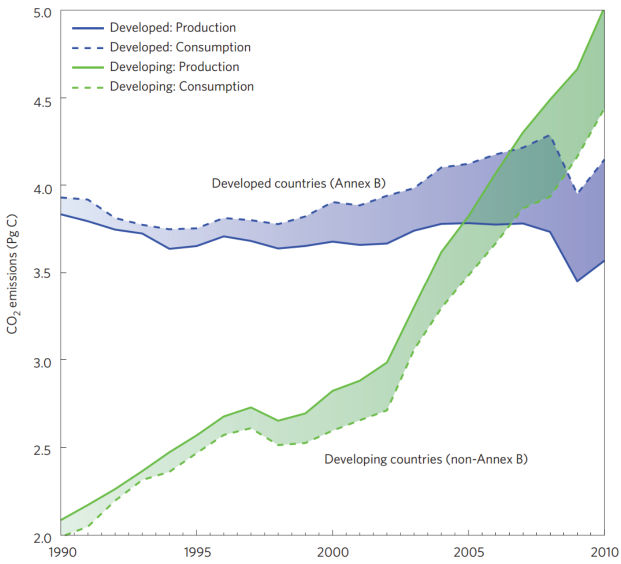

Figure 7: Production and consumption-based emissions for developed and developing nations over time. The shaded areas indicate trade balance, where exports from developing countries and imports to developed countries are increasing. Figure from (Peters et al., 2012b).

2.3. Linking emissions to trade

Several methods have been developed in order to estimate footprints or life cycle assessments of products, sectors or nations (Wiedmann, 2009, Peters, 2008, Minx et al., 2009, Peters, 2010a). This thesis focuses on using economic (input-output) data in order to allocate emissions to consumption. The construction of such consumption-based inventories often follows two steps: (1) create production-based inventories which are consistent with the System of National Accounts (SNA; United Nations (1993)), and (2) linking production to consumption via an input-output (IO) table (Peters, 2008). IO tables were originally proposed as a national system for connecting economic sectoral activities, and has later been connected to emissions of pollutants (Leontief, 1970). IO tables are constructed from what each sector (industry) requires as inputs from other sectors, and what they produce as output to other sectors or final demand (Miller and Blair, 2009). The inter-sectoral (inter-industry) flows can be thought of as production recipes to produce one unit of output in a sector; i.e. what sectors does a specific sector buy from to produce goods and services (Figure 8). The output of each industry is bought by final demand, which is usually either households, governments, or goes to investments (capital formation) or exports.

The IO table thus consists of monetary transactions, so that it connects sectoral supply and demand. From this, it is possible to follow production from raw materials to final manufacturing of a single output (e.g. a car) trough supply-chains (often referred to as structural paths (Peters and Hertwich, 2006)). These IO analyses are distinctly different from typical life-cycle assessments of products in that they are not taking into account emissions from the use of a product, or disposal of waste. Thus, they follow a "cradle to gate" perspective, from raw materials to when the products leaves the factory gate (Murray and Wood, 2010). Leontief developed a mathematical method to account for all possible structural paths in one operation, and thus include the entire supply-chain of the economy. Furthermore, it was designed to also include environmental damages, e.g. emissions to air or leakages to water, which can be directly connected to production, and thus consumption (Leontief, 1970). Such datasets are extensions of economic datasets, and are often referred to as National Accounting Matrix including Environmental Accounts (NAMEA; (Peters, 2008, SEEA, 2003)). With these connections established, UN created the System of Environmental and Economic Accounting (SEEA) in an effort to merge economic data (SNA) with environmental data.

		PRODUCERS AS CONSUMERS							
		Agric.	Mining	Const.	Manuf.	Trade	Transp.	Services	Other
PRODUCERS	Agriculture								
	Mining								
	Construction								
	Manufacturing								
	Trade								
	Transportation								
	Services								
	Other Industry								

Figure 8: Simple IO table. Illustration from Miller and Blair (2009). See section 3 for details.

The emissions are firstly allocated to producing sectors, where the total emissions from e.g. the electricity sector are known. Secondly, the emissions are normalized per unit of output of each sector (e.g. one dollar worth of electricity). Thirdly, the emissions are distributed along the supply-chain to the purchasing sectors; in this case the sectors purchasing electricity. The emissions are allocated along all possible supply-chains and ends up at final demand. The sector final demand purchases from may be very different from where the emissions originally occurred (e.g. one might purchase a book from a book store, but most of the emissions probably occurred in other sectors: forestry, electricity, industrial processing, etc.).

The concept of IO tables including environmental accounts has relatively recently been extended to include several regions, usually referred to as multi-regional input-output analysis (MRIOA) (Wiedmann, 2009, Peters, 2008). MRIOA connects supply and demand across regions at the sector level, and therefore takes international trade into account when estimating supply-chain emissions. Many recent studies have shown the differences between the production and consumption perspective (Davis and Caldeira, 2010, Hertwich and Peters, 2009, Peters et al., 2012a), and some have explored the possibility of shared emissions responsibility (Lenzen et al., 2007). Furthermore, some studies have extended the studies to further look at consequences of consumption of products, such as biodiversity loss (Lenzen et al., 2012), dependency on traded fossil fuels (Andrew et al., 2013), land-use change (Weinzettel et al., 2013), and water footprints (Hoekstra and Mekonnen, 2012). The underlying datasets and models used in this thesis to perform an MRIOA are explained in section 3. Data and modelling.

2.4. The case of Brazil

This study has a special focus on Brazil, being part of the project *"Quantifying the global socio-economic and policy drivers for Brazil's contribution to global warming"*. There are several reasons to why Brazil is of global importance: (1) it was the world's 7th largest economy in 2013 (World Bank, 2014), (2) it was the 6th largest GHG emitter including deforestation in 2011 (CAIT, 2014) and (3) it has been one of the main actors in the climate negotiations.

First, Brazil is one of the most important transition economies, being part of the BRICs (Brazil, Russia, India and China) group, with a recent peak of GDP growth in 2010 of 7.5%. Due to large growth in agricultural production and export shares over the last decade, Brazil was the world's largest exporter of beef, coffee and sugar, and the second largest soy bean exporter in 2010 (FAO, 2014). This historic economic growth has generally been closely linked to increasing emissions of GHGs (De Freitas and Kaneko, 2011).

Second, Brazil ranked as the world's top 14th fossil fuel emitter in 2011, with 443 Mt CO_2 emissions (CAIT, 2014). However, by normalizing the emissions per capita, they drop to 98th place, with 2.25 t CO_2 per capita. Although the Brazilian population has risen steadily to currently around 200 million (IBGE, 2014), the main reason for the low capita footprint is the unusual energy matrix (energy sources). Around 60% of primary energy consumption was based on fossil fuels in 2011, while around 40% came from renewable energy sources (EIA, 2013). Hydroelectric power generation dominates, being responsible for 35% of the total energy consumption. While hydropower is the source of around 15% of the global electricity consumption, 84% of the Brazilian power was based on hydroelectric power plants in 2009 (Brazil, 2010, Pao and Fu, 2013).

While fossil fuel emissions per capita have been relatively low, emissions from LUC have been very large, mostly due to deforestation of the Brazilian Amazon. The deforestation is mostly driven by expansions of pasture and croplands, in order to meet demand for agricultural products (Barona et al., 2010). Deforestation rates hit a peak in 2004, which made Brazil the world's 3rd largest emitter of GHGs including deforestation (INPE, 2012, CAIT, 2014). Since then, the Brazilian government has managed to significantly reduce its emissions due to near real-time monitoring of deforestation via satellites, area protections and law enforcements (INPE, 2012, Silva, 2012). Deforestation rates have declined by 75% from 2004 to 2010 (INPE, 2012), and, consequently, emissions have decreased from 1250 to 560 Mt CO_2 (Paper 1).

The economy has historically been driven by domestic demand and consumption, but between 1998 and to 2013, the share of export in Brazils GDP has increased from 7% to 13% (The World Bank, 2014). A more detailed breakdown reveals that exports of meat and soybeans have increased by 500% and 250%, respectively, thus the demand for agricultural land is high (FAO, 2014). This increasing international demand may undermine the international effort of protecting the rainforest, led by payments from Norway (Nepstad et al., 2009). Thus, studies have suggested introducing additional carbon costs on products, excluding products from deforested areas, or accept payments from other governments as compensation for protection (Zaks et al., 2009, Nepstad et al., 2009).

Third, Brazil has been relatively active in the international climate negotiations due to its unique position (being a developing but also emerging economy, having a relatively clean energy matrix, and having 16% of the world's forest), and has recently changed its climate policy position to become much more pro-active (Viola, 2004). Historically, Brazil has been rejecting emission reduction commitments, similar to other developing (G77) nations, which is usually based on the arguments that early emitters (developed nations) should take most responsibility since they historically have emitted more, and that developing countries should be allowed to develop their economy in order to lift the population out of poverty before committing to emissions (and thus economic) reductions (Kasa, 2013, Kasa et al., 2008). Additionally, technological transfers and financial aid from developed to developing nations has also been suggested, to help with mitigation and adaptation. These arguments were embedded in the Brazilian proposal (den Elzen et al., 1999), and Brazil was also heavily involved in the design of the Clean Development Mechanism (CDM) that was defined in the Kyoto Protocol, where they avoided deforestation emissions to be included in the CDM (Kasa, 2013).

After 2005, several economic opportunities provided strong incentives for a more pro-active stand: increasing trade and engagement in international trade talks (due e.g. to discussions in the US about increasing taxes on imports from countries without emission reduction commitments), the emergence of compensating mechanisms through e.g. REDD (Reduced Emissions from Deforestation and Forest Degradation) (Kasa, 2013), and increasing understanding and recognition of climate change impacts on the Amazon rainforest (Lewis et al., 2011, Malhi et al., 2009). Negative economic impacts from climate change is expected, especially from the agriculture sector which will be directly affected (Margulis et al., 2011). Thus, the Amazon Fund was established in 2008, through which Norway has donated 636 million USD, and a promise of another 364 million if further reductions are met (Amazon Fund, 2012). Additionally, in 2009, Brazil declared that it would voluntarily cut emissions in 2020 by more than 35% of projected emissions (Kasa, 2013, Brazil, 2010). This includes emissions from LUC, which are also the cheapest to reduce (Gurgel and Paltsev, 2013). Furthermore, Brazil declared that it would consider legally binding emission reductions at the 17th session of the Conference of the Parties (COP) to the UNFCCC in 2011 in Durban, South Africa, if other developed countries also joined (Hochstetler and Viola, 2012).

Although Brazil is presently one of the leading developing nations with a pro-active climate policy stand, it has to tackle large challenges (deforestation rate estimates for 2013 currently show a nearly 30% increase compared to 2012 (INPE, 2012), and economic projections for the next years are looking to some extent dim, with GDP growth slowing down and unemployment expected to rise (IMF, 2014)), but should use this opportunity to create economic incentives and strong sanctions in order to encourage changes to its emissions (Silva, 2012). Although Brazil is of global importance due to its large emissions and large economy, and possibly large effect on other developing countries in the climate negotiations, few studies have connected Brazil's emissions with the consumption leading production, and thus estimated the international drivers of increasing domestic production and emissions. Therefore, this thesis has a focus on Brazilian emissions and trade, and shows Brazilian results drawing from Paper 1-4 in section 4.

3. Data and modelling

This section briefly discusses the datasets and methods used in the papers. The Emissions data section first lays out the deforestation data and carbon cycle modelling that was done to create emission estimates from deforestation in Brazil in Paper 1 and 2. The Economic data section shows the datasets used in the global analysis in Paper 3 and 4, while the next sections briefly explain the concepts of input-output analysis and uncertainty estimations using Monte Carlo simulations.

3.1. Emissions data

3.1.1. Land-use change

The first study (Paper 1) focused on Brazilian deforestation, happening in the Amazon rainforest (Figure 9). The Brazilian National Institute for Space Research have two satellite systems, continuously monitoring the rainforest for surface cover changes (INPE, 2012). Paper 1 used official annual deforestation rates (in square km) covering the Brazilian Amazon, and the analysis consider emissions occurring over the two decades from 1990 to 2010. Due to the agricultural practices, where a part of the forest loss were left for slash, CO_2 emissions would occurred several years after the deforestation happened (Ramankutty et al., 2007). Because of this, deforestation rates back to 1977 were considered, when observations started (INPE, 2012).

Estimating carbon emissions from deforestation rates was done using a simple carbon cycle model, which included the shares of burnt and decay of newly deforested trees, following Ramankutty et al. (2007). Regrowth and secondary deforestation was also taken into account to estimate net emissions. The decay of biomass and cleared regrowth creates inertia in the emissions, distributing them over many years. Since 1977 was the first year of INPE's deforestation database, the analysis of 1990 included 13 years of legacy emissions, including deforestation and the following emissions happening in 1990. For consistency, the following years of the analysis also had 13 years of legacy emissions. Deforestation rates were multiplied with carbon in biomass, in order to estimate CO_2 emissions (Saatchi et al., 2007, Zaks et al., 2009). This is only one of the more uncertain aspects of the analysis, as carbon density in the rainforest has a very large range. In an effort to improve the accuracy of the estimates the study used different values for each state for both carbon density and agricultural practices (Galford et al., 2010).

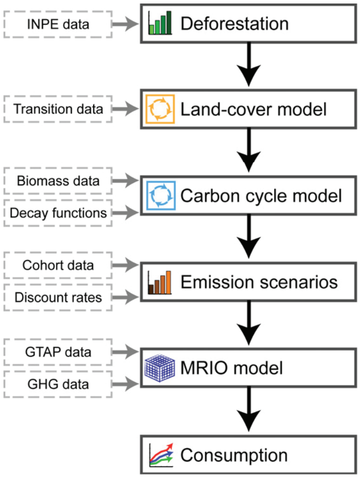

Figure 9: Flow chart of connected models and datasets in Paper 1.

Deforestation and burning of trees cause emissions of other pollutants as well, although little data exist on a regional level (Penman et al., 2003, van der Werf et al., 2010). Paper 2 is based on the same deforestation datasets, however, it goes back to 1961, assuming an interpolated run-up until INPEs numbers starts at 1977, following Ramankutty et al. (2007). The analysis starts at 1970, where emissions from deforestation have started to build up.

3.1.2. Other emissions

Paper 3 and 4 have a global approach, and thus use global emissions divided into regions and sectors. In order to capture non-CO_2 emission's effect, which collectively were responsible for roughly 50% of absolute CO_2-eq. emissions compared to CO_2 using GTP50, the studies includes additional well-mixed greenhouse gases (WMGHG) and short-lived climate forcers (SLCFs). The emissions data is from the EDGAR database (Emissions Database for Global Atmospheric Research) (Andrew and Peters, 2013, European Commission, 2011), with the exception of organic carbon and black carbon (Shindell et al., 2012). The dataset includes CO_2, CH_4, NO_X, SO_2, NF_3, CO, N_2O, NMVOC, NH_3, SF_6, 8 PFCs and 11 HFCs for the year 2007. Organic carbon (OC) and black carbon (BC) data are from the years 2005 and 2010, thus we use a weighted average to estimate 2007 emissions, not including biomass burning.

The data is mapped to 57 sectors in 129 regions, which is the coverage of the economic dataset (discussed in the next section). The CO_2 emissions cover anthropogenic sources, not including short-cycle emissions from burnt biomass as this is considered to be absorbed by regrowth within a short time. The dataset does, however, include emissions from agricultural waste and savanna burning (European Commission, 2011). For the ozone precursors, CO, NO_X and NMVOC, we include the indirect effects they have on ozone formation, changing CH_4 concentrations and induced O_3-effect (Paper 4). Additionally, the indirect effect of SO_2 on clouds are included by scaling the metric values by 175% of the direct effect (Aamaas et al., 2013b).

In an effort to make Paper 3 and 4 more policy relevant, the emissions are converted to global temperature change using the GTP50 metric. The metric is parameterized to approximate complex climate models and their behavior, thus the parameters (such as climate sensitivity and its time horizons) used in the metric can potentially have large effects on the results (Olivié and Peters, 2013). Paper 3 and 4 use pollutant parameters from (IPCC, 2007b) and Fuglestvedt et al. (2010), to be comparable with a large part of the literature. Additionally, Paper 3 and 4 use updated parameters of the IRF of temperature derived from CMIP5 data (Olivié and Peters, 2013), which includes estimates of uncertainty. The IRF_{CO2} is also updated according to Joos et al. (2013), which is based on 15 state-of-the-art carbon-cycle models.

3.2. Economic data

Allocating emissions to consumers through the global-supply chain requires an economic model, which may be based on various economic data. The model used in the work presented in this thesis (Paper 1, 3 and 4) is based on datasets from the Global Trade Analysis Project (GTAP), which are based on national input-output (IO) tables to create a consistent representation of the global economy (Narayanan et al., 2012). The GTAP database is one of the most detailed in terms of IO tables covering multiple regions (depending on version number), 57 sectors and several years. The IO table contributions are based on voluntary submissions by GTAP members, which means that they may include inconsistencies in definitions, have a large range of different currencies and may not be from the same year as the based year of the GTAP database (Andrew and Peters, 2013). Thus, the input data is balanced and harmonized so that essential IO characteristics are met (e.g. global exports must equal global imports), and is explained to some extent elsewhere (McDougall, 2001).

The submitted IO tables are adjusted according to trade, macroeconomic and protection data from numerous sources, and the final datasets also includes several satellite accounts covering energy consumption, GHG emissions, land-use and forestry (Peters et al., 2011b, Andrew and Peters, 2013). Measurements of the inconsistencies for version 6 (with base year of 2001) are generally found to be minor (Andrew and Peters, 2013), however, measurements for more recent versions (7 and 8, for the years 2004 and 2007) have not been published, thus uncertainty information is very limited (Paper 4 investigates how estimated uncertainty from economic data affect results on consumption-based emissions).

Such IO tables have clear limitations; e.g. they are only available for a selection of years (which means that they are just a snapshot of the economy at one point in time), there is considerable time-lag between the base year and when they are published (version 7, covering the year 2004, was released in 2008) (Peters et al., 2011b), large sectors means that they represent industry averages (Murray and Wood, 2010), and little information about uncertainties or to what extent adjustments are done on initial data. However, they also have clear advantages in that they have relatively large sector and region details, the finished GTAP database is already balanced, thus no further balancing should be necessary (Peters et al., 2011b), and using IO data solves the *boundary issue* by taking into account the entire supply-chain, which implies no double counting (Murray and Wood, 2010).

Paper 1 use versions 5, 6, 7 and 8 of the database, to create a time series of trade (see next section for details). Paper 3 and 4 use the recent version 8 of the database, covering the world economy for 2007, with 129 regions. While the newer versions include more regions details (from 87 to 129 regions from version 6 to 8, respectively), the sector details are constant at 57. Several methods exists in estimating final consumption (e.g. Emissions Embodied in Bilateral Trade (EEBT) and multi-regional input-output (MRIO) model, see (Peters, 2008)), and they rely on different assumptions. Paper 1use an EEBT methodology (see next section) as it extrapolates data over several years, while Paper 3 and 4 use an MRIO model, as this is arguably more suited for analyzing emissions allocated to final consumption, due to the treatment of intermediate consumption (Peters, 2008). While GTAP does not provide an economic model (EEBT or MRIO), which is necessary to allocate emissions to consumers, it can be derived from the GTAP database. The next section briefly explains the basic modelling concepts used in this work.

3.3. Economic models

Creating an economic model in order to allocate emissions to consumers can be done in several ways (see Wiedmann (2009) for a review of MRIO models). This work presented here relies on two major approaches; (1) creating a time series of bilateral trade (EEBT model) for multiple years (which was done in Paper 1), and (2) enumerating the global supply-chain (MRIO model) for a single year (which is used in Paper 3 and 4). The EEBT model used to allocate CO_2 emissions from deforestation in Paper 1 can be considered a variant of the MRIO model, being based on monetary bilateral trade statistics from the MRIO table (see Figure 10), which allocates emissions occurring in production for export to other regions (Peters, 2008). This does not include emissions from multiple layers of imports that are used in the same production, thus it does not take into account the full global supply-chain. This can be done using a full MRIO model, which connects an infinite number of production-consumption paths. The differences between the two models have been shown to be more than 20% for some regions, although the differences are only in allocation, thus the global emissions are the same (Peters, 2008). However, although the EEBT model allocates intermediate imports to the producing regions, the EEBT model is simpler and is more comparable with GDP data. Thus, a few years of detailed EEBT data can be used to create a time-series of trade (TSTRD) by scaling the data by GDP, bilateral trade and emission statistics (Peters et al., 2011c).

In the case of Paper 1, only CO_2 emissions from Brazilian deforestation are allocated through the EEBT model. The EEBT method only considers direct trade flows, and thus our analysis does not consider redistribution from further downstream processing. The TSTRD in Paper 1 is based on the EEBT data for the available years (1997, 2001, 2004 and 2007), and scaled from 1990 to 2010, which is an extension of the study by Peters et al. (2011c).

Creating an MRIO table from the GTAP database follows a numbers of steps, and has been explained in other papers (Peters et al., 2011b, Andrew and Peters, 2013). The GTAP database is built on numerous datasets, which can be connected through accounting identities in order to construct the MRIO table, which can be expressed as

$$x = Z + y \tag{1}$$

where x is the output of the economy, Z is the intermediate consumption and y is total demand (consumption).

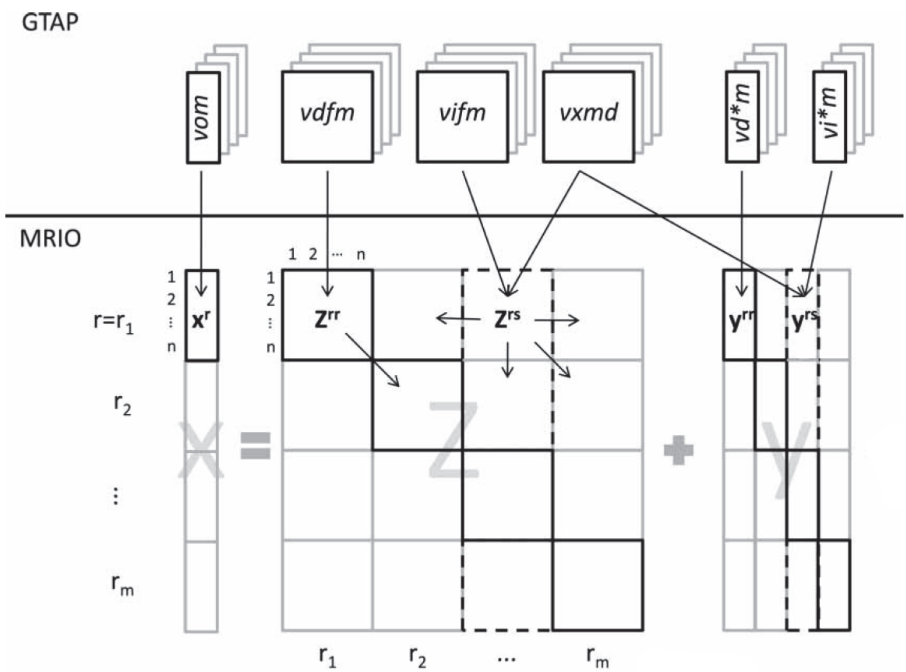

Figure 10: Constructing an MRIO table from GTAP data. Simplified version of Figure 1 from Peters et al. (2011b).

Domestic production for region r can then be explained by adding domestic firm (*vdfm* block in Figure 10), household, government and investment purchases in all sectors together, which become the diagonal blocks (Z^{rr}) in the Z matrix (Peters et al., 2011b).

Additionally, off-diagonal blocks (Z^{rs}) explain imports and exports from all sectors from and to region r. The total domestic demand (y^{rr}) is based on total domestic purchases except from firms, which occupy the diagonal blocks in the y matrix. International demand (y^{rs}) is based on imports to region s. The decomposed relationship can be expressed as

$$x = Ax + y \tag{2}$$

where A is the inter-industry requirements matrix (recipes for production of one unit of each sector). Computationally, this is performed using Leontief's famous input-output relationship (Leontief, 1970, Peters and Hertwich, 2004):

$$x = (I - A)^{-1}\, y \tag{3}$$

where $(I - A)^{-1}$ is usually referred to as the Leontief inverse (or total requirements matrix) L, which enumerates the entire supply-chain's infinite number of paths. This includes all layers (usually called tiers) of production from indirect effects to direct effects in production and the resulting emissions of e.g. producing a car. This step (matrix inversion) is where the computational requirements are the largest, and pose a significant barrier for the number of Monte Carlo runs in Paper 4, since this has to be done in each iteration of the analysis. The total emissions f (being multi-pollutant temperature change from all sectors in Paper 3 and 4) can be normalized to one unit of output in each region and sector, giving the direct emissions F_i in column i:

$$F_i = f_i / x_i \tag{4}$$

The total emissions can then be allocated to producing and consuming regions and sectors of the economy based on the production requirements of each sector and total demand (where L is the Leontief inverse explained above):

$$f = F * (L\, y) \tag{5}$$

The consumers in f are the nations and sectors that final purchases are done from. Allocating emissions trough the economic models adds additional uncertainties to the results as emissions statistics become dependent on trade data. The next section discusses uncertainties in production and consumption-based emissions, which is the topic of Paper 4.

3.4. Uncertainty analysis

The work presented in this thesis extends the analyses of uncertainties in human-induced temperature change by taking into account numerous pollutants and additionally connecting regional production with regional consumption at the sector level. Paper 3, similarly to Höhne et al. (2008), investigates the results dependence on parameter choices, but instead looks at how allocations of current emissions differ from using production or consumption, and GWP or GTP. Paper 4 builds on this by, similar to Prather et al. (2009), investigating the uncertainties of emissions and climate response, using current emissions. Furthermore, the analysis assess if the economic data used to convert production emissions to consumption-based emissions introduce additional substantial uncertainties. Paper 4 also discuss that the uncertainties for national emissions overlap, using both GTP and AGTP, suggesting that the ranking is uncertain (which is similar to Höhne et al. (2008) who also found large uncertainties, especially for Brazil and India; see next section for Brazil-specific results).

Emissions of pollutants, converting emissions to temperature change and using economic data to allocate emissions to consumers introduce various uncertainties from datasets and model parameters. This is important in the context of climate policy, as support for mitigation of emissions with highly uncertain consequences can be very difficult (Barrett and Dannenberg, 2012). This section briefly explains the individual uncertainties, and additionally how this is used to estimate propagation of uncertainties to the final results in Paper 4 (Figure 11).

Several approaches exist in assessing the uncertainty of emissions, such as comparing datasets based on independent methods and from different sources (Marland et al., 2009). These methods are best suited on the global level. On more detailed levels, however, datasets may be more difficult to compare with different aggregations and different spatial and temporal coverage (Macknick, 2011, Andres et al., 2012). Thus little data exist on uncertainties on sector and regional level for individual pollutants. The estimates that have been made, indicate much higher uncertainties on regional and sectoral levels

(Andres et al., 2012, Smith et al., 2010). For mitigation policies, additional uncertainties may be significant, although not considered here, such as where emission reductions take place and what effect it has on emissions of other pollutants (Berntsen et al., 2006).

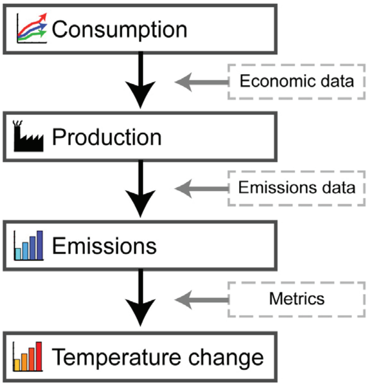

Figure 11: Schematic flow-chart of activities and datasets included in the uncertainty discussion (figure from Paper 4)

The most important contribution to climate change in terms of anthropogenic emissions, CO_2 from fossil fuels, is known to have an uncertainty of around ±8% (using 90% confidence interval) on global emissions (UNEP, 2012), although much higher regional differences are found (IPCC, 2014a). SO_2, SF_6, HFCs and PFCs have uncertainties between ±10% and ±17%, while CH_4 and N_2O exhibits larger relative uncertainties in the range of ±21%–±25% (UNEP, 2012). Generally, uncertainties are larger for pollutants that does not directly relate to activity levels, especially for CH_4 (e.g. fugitive and biogenic emissions), N_2O and LUC (see below) (IPCC, 2014a).

CO_2 emissions from land-use change (including land-use and deforestation), however, have much greater uncertainty due to uncertainties in deforestation rates, carbon stock in biomass, agricultural practices, carbon cycle modelling, etc. (Houghton et al., 2012, Ramankutty et al., 2007, Saatchi et al., 2007). LUC emissions were responsible for around 12% of global emissions in 2008 (Le Quéré et al., 2009), but was also one of the largest sources of uncertainties in the global carbon cycle (Aguiar et al., 2012). Although the relative emissions from LUC have declined in the last years, as it was estimated to be approximately 10% of fossil fuel emissions in 2010 (IPCC, 2014a), this is mainly due to large increases in fossil fuel use, thus LUC emissions are still important. While some estimates for the last decades show a small decline in global LUC emissions, absolute uncertainties are estimated to be roughly the same, thus increasing the relative uncertainties in recent years (IPCC, 2014b). Several significant sources of uncertainties also exist in the understanding of the deforestation process, which may be very region dependent (Ramankutty et al., 2007): (1) land-cover dynamics, (2) inclusion of legacy emissions, and (3) fate of cleared forests. Houghton et al. (2012) estimated a global uncertainty of ±45% for the years 2000-2009, which was based on four studies for the last decade, including expert judgments on data uncertainty and the incomplete understanding of the various processes. The new IPCC AR5 report estimates even higher uncertainties of nearly ±75% (IPCC, 2014b), suggesting that the uncertainty estimates are not robust.

The conversion of emissions to global temperature change using a metric introduces further uncertainties. Metric calculations depend on impulse response function (IRFs) which are parameterized according to complex climate models, such as the IRF for temperature and CO_2, which may be associated with large uncertainties (Olivié and Peters, 2013, Reisinger et al., 2010). Paper 4 uses the Global Temperature change Potential (GTP) to put all pollutants on the same scale. The GTP metric values are normalized by absolute GTP values of CO_2 (see section 2.1. Climate change), making the uncertainties in CO_2 important for other pollutants GTP uncertainty (Aamaas et al., 2013b). While studies have found that the GTP has higher uncertainties than e.g. the global warming potential (GWP), as it also includes uncertainties in the climate system response to increased RF (Aamaas et al., 2013b, Myhre et al., 2013a) (Skeie et al., 2013), the GTP is used in Paper 3 and 4 to capture the policy-relevant temperature change of emissions.

Uncertainties investigated in Paper 4 are based on recent results from CMIP5 data which is based on several models (Taylor et al., 2012, Olivié and Peters, 2013). Of the datasets covered in Olivié and Peters (2013), the CMIP5 data has the largest uncertainties for most of the parameters, thus the spread of the metric component in Paper 4 probably indicate the high-end of uncertainties for the climate response and CO_2's effect. Additionally, each pollutant has RF and lifetime parameters which also include uncertainties. Uncertainties in RF estimates are known for most pollutants, which is based on how well their direct and indirect processes are understood, and how well model estimates coincide (Myhre et al., 2013a, Myhre et al., 2013b). Literature on uncertainties in lifetime estimates, however, is very scarce, and is mostly assumed in Paper 4. Between 1 and 100 years time horizon, the analysis find that a small change in lifetime would not significantly change the total uncertainties for most pollutants, as the lifetime is either too small or too long to have any significant effect.

Recently, two studies have investigated the uncertainties in human made emissions and temperature change (Prather et al., 2009, Höhne et al., 2008). The first study found temperature increase of 0.11°C ± 27% (using 68% confidence interval, equivalent to ±45% using 90% confidence interval) in 2003, due to emissions from developed nations in the years 1990 to 2002. Prather et al. (2009) used the MAGICC simple climate model, and found that the uncertainties on the final results were mostly from the climate modeling (similarly to the IRF of temperature for the GTP). Höhne et al. (2008) compared nation's relative contributions to emissions and their uncertainty, and found that the total uncertainty was dominated by uncertainties in historical emissions. Additionally, they found that changing parameters in the calculations were most relevant for countries that have a different GHG emission profile than the world average, as they were comparing relative contributions. This is especially important for Brazil, as its large CH_4 emissions from agriculture are highly dependent on e.g. the metric and its time horizon.

Surprisingly few studies have investigated the uncertainties in economic data which is necessary to model monetary transactions and international trade, and are further used when allocating emissions to consumers (Lenzen et al., 2010, Lenzen, 2000, Weber, 2008). The GTAP database is a consistent representation of the global economy for a single year, which is based on input-output data from numerous regions which have to be harmonized in order to be consistent (Andrew and Peters, 2013, Peters et al., 2011b, Narayanan et al., 2012). Few details of this process has actually been published, but tables showing the input numbers and the adjusted numbers for an earlier version have been made available (McDougall, 2001). These adjustments (which are based on conflicting estimates) can be used as a proxy for uncertainties in the final dataset. According to the table, larger sectors have smaller relative uncertainties than smaller sectors (Lenzen et al., 2010). Since little data exist, uncertainties are estimated in Paper 4 using the table as a basis for establishing a relationship between sector size and uncertainty.

Another study has compared several MRIO and EEBT model results, which they found to be sufficiently robust, although regional differences in excess of 10% was found in some cases (Peters et al., 2012a). Uncertainties may also arise from different definitions and aggregations (Solli and Peters, 2010, Kanemoto et al., 2011, Andrew and Peters, 2013). The few studies that have undertaken the task of investigating uncertainty sources and propagation in integrated assessments models, have either not looked at temperature or consumption-based emissions, or looked at a specific case study (Wilting, 2012, Lenzen et al., 2010, Wiedmann, 2009). Only simpler MRIO models have been tested using MC analysis, but no thorough analysis of an entire MRIO model has ever been investigated. This is a gap in the literature, which includes detailed uncertainty in economic data and how different supply-chain models differ (IPCC, 2014a). It has also been discussed that the consumption view is too uncertain, since it is based on economic models of trade (Peters et al., 2011c). Therefore, an analysis (such as shown in Paper 4) is much needed.

Paper 4 analyses the uncertainty in the consumption footprint from the different components (emissions data, metric parameters and economic data) using Monte Carlo (MC) analysis. The MC analysis is a method of assessing how uncertainties in input parameters affect the uncertainty of the end results (Granger Morgan et al., 1990). The input parameters of a model is randomly perturbed according to known or estimated uncertainty distributions, and then the model is run with new random samples many times to get a distribution on the results. Thus, it is an ideal technique to assess parametric uncertainties, and have been used extensively throughout the literature (Wiedmann et al., 2008, Peters, 2007, Bullard and Sebald, 1988). To estimate error propagation, the process in Paper 4 randomizes all input datasets used to construct the full MRIO model before constructing it in each MC iteration, instead of randomizing the constructed model. The individual contributions to uncertainties in the end results are found by running the MC analysis with only perturbations on selected variables. Brazil specific uncertainty results are shown in next section, while section 5. Summary of papers gives an overview of the results in Paper 4.

4. Brazil

This section draws on results from Paper 1-4 to estimate Brazil's emissions and contribution to global warming. Additionally, emissions are allocated to sectoral consumers, thus exploring the drivers of Brazilian emissions. The analysis explores Brazil's role in international trade, and the embodied emissions to sectors and regions. Uncertainties in the results are estimated from the analysis done in Paper 4, while deforestation (land-use change; LUC) emission uncertainties are derived from the literature. The final sub-section discusses the policy implications of these results, and the outlook. This chapter will later evolve into an article and be published under the tentative title of *"Brazil's consumption-based contribution to global temperature change and its uncertainty"*.

4.1. Contributions to global warming

Historically, Brazil has had relatively low energy-related carbon-intensities due to its unusually high mix of renewable energy sources (Paper 2). Although energy-related emission have more than quadrupled from 1970 to 2008, about 45% of the energy is renewable, thus the carbon intensity is much lower than other comparable large economies (China, India, USA, Russia, Germany and Japan).

Brazilian emissions have historically been dominated by emissions from forest loss (Figure 1 in Paper 2). Although annual deforestation rates, and consequently emissions, have seen a dramatic decrease since 2004, it was still the largest source of emissions in 2007 due to inertia in forest decay emissions (Paper 1). The Brazilian government published numbers for 2005, including deforestation, which was estimated at 77% of the national estimate (total of 1638 Tg CO_2). The model developed in Paper 1 estimates direct deforestation emissions (everything is burnt) in 2005 to be around 1365 Mt, making our estimates 8% higher than the reported estimate. However, when including legacy emissions and regrowth, the 2005 estimate is brought down to 1020 Mt CO_2.

Due to the high agricultural activities, other emissions such as CH_4 and N_2O are also very important for Brazils total emission. Brazil had the 5th largest methane emissions in 2007, being responsible for 6% of global methane emissions, coming mostly from agricultural and petroleum sectors (European Commission, 2011). Short-lived cooling pollutants, such as NH_3 and NO_X, are also important to the agricultural sectors. Such short-lived pollutants are difficult to compare with other gases, as their relative effect is highly dependent on non-scientific choices (see earlier discussion on metrics).

In the second national communication of Brazil to the UNFCCC in 2010, the Brazilian government objected to the use of GWP100 for comparing emissions of different pollutants, as they claim it puts too much weight on short lived pollutants such as methane (Brazil, 2010). As Shine (2009) pointed out, methane emissions from Brazil in 1994 were 110% of the CO_2 emissions using the GWP100, while it was only 15% using GTP100. The Brazilian government therefore sees the GTP metric as more suitable for comparing gases, while it also relates to temperature change and thus is more policy relevant. For 2007, the equivalent estimates for methane are around 110% and 25% (using IRF parameters from Paper 3 and 4). The papers presented in this thesis often use GTP50 as metric, thus placing more weight on short-lived pollutants than then equivalent 100 year perspective, but less weight than the GWP100. Using GTP50, Brazilian methane emissions were 60% compared to CO_2 emissions. Overall, non-CO_2 emissions represents (in absolute values using GTP50) more than 60% of total emissions.

The largest emissions in Brazil happen in agriculture, energy-intensive manufacturing and households sectors, making them responsible for nearly 80% of the total emissions (Figure 12). LUC (deforestation and decay of waste from deforestation), however, is much larger than any other single sector, and for 2007 is estimated at 108% of total emissions excluding LUC, or 767 Mt CO_2. This is from a combination of sources, where the energy- and agriculture-related emissions are from the EDGAR database, while the LUC emissions are estimated from Paper 1. Even though LUC emissions are ultimately allocated to soy beans and meat (agricultural), we have shown LUC emissions separately for visibility.

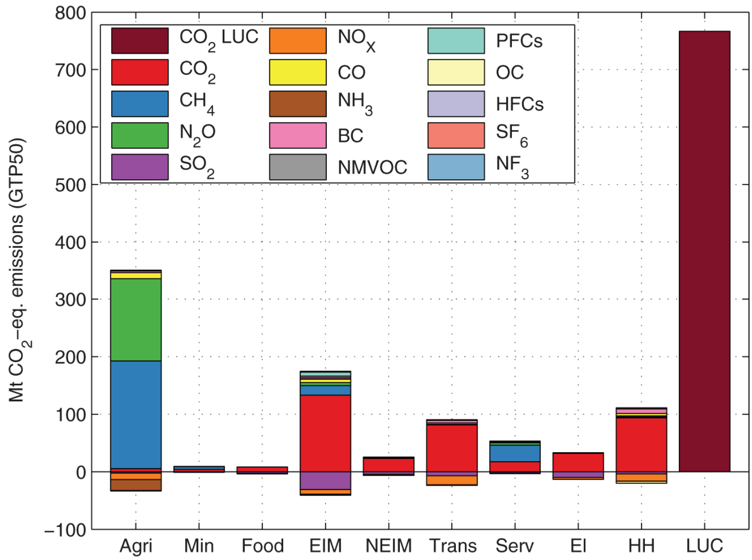

Figure 12: Sectoral production emissions in Brazil for 2007. LUC emissions are based on calculations from Paper 1, while the other sectors are based on calculations from Paper 3 and 4.

The LUC emissions are a result of direct emissions from forest burning, decay (mostly from slash) and regrowth. Following Paper 1, this emission estimates includes 13 years of legacy emissions, thus a part of the emissions occurring in 2007 can be traced back to deforestation happening in 1994. As stated in Paper 1, it is a fair assumption to allocate all LUC emissions to Brazilian sectors containing soy beans and cattle, as most of these activities take place on either newly or previously deforested areas (Barona et al., 2010). Using the land-use transitions explained in Paper 1 (where emissions are allocated according to the amount of time an agricultural activity takes place on the newly deforested area), soy beans are allocated 156 Mt CO_2 and cattle meat 610 Mt CO_2 for the direct and legacy emissions. These shares depend on the year of deforestation, as the agricultural practices between the Brazilian states differ and their deforestation rates change with time (Zaks et al., 2009, INPE, 2012).

4.2. Emissions embodied in trade

Allocating LUC emissions to their respective Brazilian sectors, and then allocating emissions to regions and sectors using the MRIO model, we find that most of the Brazilian LUC emissions end up in products being consumed domestically (71%). This is, however, a simplistic view of a complex picture; legacy emissions are then allocated according to trade shares of 2007, thus e.g. China is allocated the responsibility for previous deforestation (1994-2006) due to its trade in 2007, although the deforestation in previous years might have been driven by other countries (legacy emissions allocated to 2007 was responsible for the majority, 65%, of that years emissions). When allocating legacy emissions according to trade shares of their respective base years from the time-series of trade dataset developed in Paper 1, Brazil is allocated 72%, China 5%, Russia 2%, Netherlands 2% and Italy 2% of total LUC emissions. EU27, collectively, is allocated 10%.

Such allocations are based on value judgments, and no allocation is wrong or right. It can even be argued that there is a time lag between consumer demand and increasing production, thus allocating one year's emissions to the same year's consumption might be considered unfair. However, most countries have had a relatively smooth change in imports from Brazil over the two decades. China is an outlier, and has increased its imports of soybeans from 7% in 1990 to 23% in 2010 of total LUC emission allocated to soybeans. With beef, most countries have been relatively stable except Russia, which has also increased its imports from near zero to 4% of total emissions. Brazil generally shows an increase of trade shares of production for both soybeans and beef, where exports has increased from 38% to 54% for soybeans and from 12% to 19% for beef from 1990 to 2010.

For consistency with non-LUC emissions and to show the current drivers of LUC emissions, the rest of this analysis assumes that consumption happening in 2007 can be attributed to the emissions happening in 2007. Figure 13 shows sectoral consumption, including emissions from LUC (mostly appearing in the agriculture and food sector). The inclusion of emissions from LUC increases the footprint of the agriculture and food sectors with more than 130% and 230%, respectively. Brazilian emissions (including LUC emissions) are smaller using consumption-based emissions (1260 Mt CO_2-eq.), than the corresponding production emissions (1480 Mt CO_2-eq.). Thus, Brazil is a net exporter of emissions, mainly due to LUC emissions. By excluding LUC, Brazil has around 700 Mt CO_2-eq. for both production and consumption-based emissions. Excluding LUC emissions also affects the food sector, which in a consumption view becomes second largest, after the service sector.

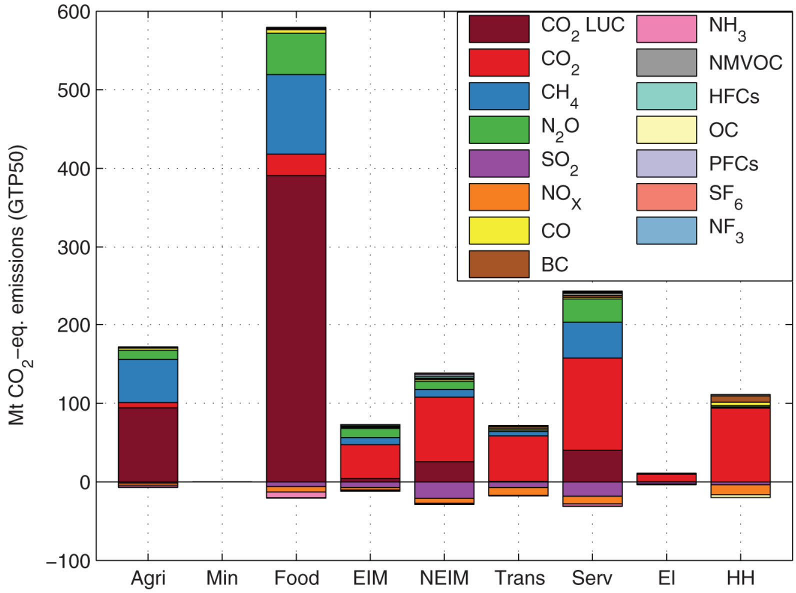

Figure 13: Consumption-based emissions for Brazil in 2007, including LUC emissions allocated to soy beans and cattle.

Sectoral imports and exports (Figure 14) suggests 330 Mt of total emissions are exported while 110 Mt are imported, thus leading to a trade balance of around 220 Mt CO_2-eq. Excluding LUC emissions only change export emissions, which is decreased to 120 Mt. Only looking at LUC emissions, reveals that around 560 Mt is consumed domestically. Agricultural and food-based sectors dominate emissions embodied in exports, as this is where LUC emissions appear (especially in the cattle, oil seeds and sugar cane sectors). Energy-intensive manufacturing, specifically petroleum and coal products and chemical, rubber and plastic products, is the third largest aggregated sector. Overall, domestic production that is exported is responsible for 22% of Brazil's production emissions. On the import side, manufacturing (especially machinery and equipment, and chemical, rubber and plastic products) and transport (air, sea, road and rail transport, transport equipment) sectors are important. In total, imported products that are originally produced elsewhere is responsible for nearly 8% of total production emissions.

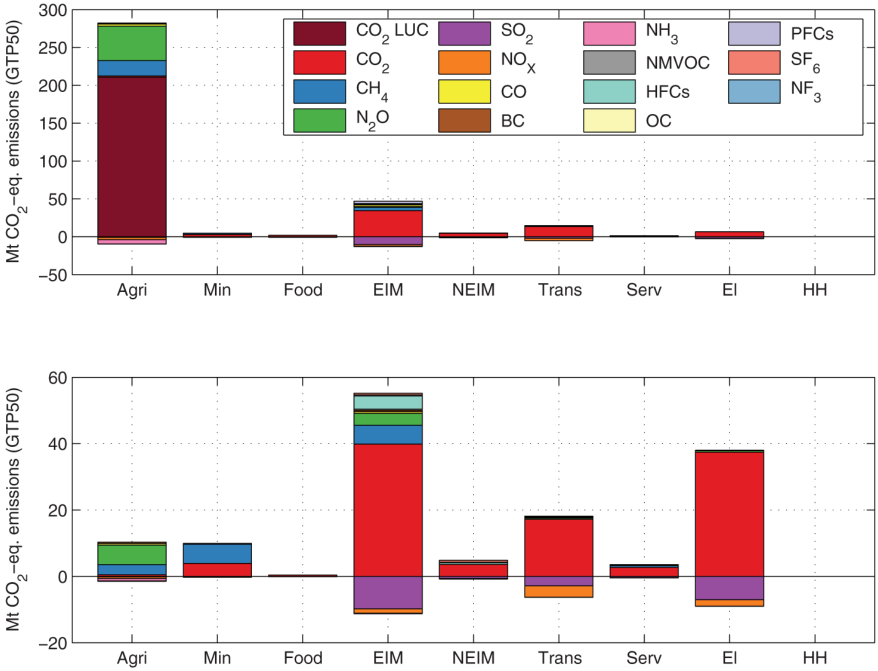

Figure 14: Sectoral trade by emitting sectors. Top figure shows emissions embodied in exports (sectors producing and emitting GHGs to produce goods that is consumed abroad), while the bottom figure shows emissions embodied in imports (showing which sectors emissions occurred in abroad). Overall, Brazil is a net exporter of emissions. Note that emissions from LUC in other countries are not included.

On a regional basis, the top importers of Brazilian beef are Russia (4% of total production), Italy (1.3%) and Venezuela (1.1%), while Brazilian soy beans are mostly exported to China (19%), Spain (4%) and France (4%). Figure 15 shows the top regions that Brazil exports to and imports from, where the agriculture sector in exports consists mostly of emissions linked to soybeans and beef due to Brazilian deforestation In 2007, domestic consumption of Brazilian beef and soy beans dominated with 81% and 35%, respectively (combined, 72% of total LUC emissions was consumed in Brazil). Thus, deforestation emissions are mostly driven by domestic demand.

Imports are on a much smaller scale, as only exports include emissions from Brazilian LUC. The main imported goods are from China (22% of total imports), USA (15%) and Argentina (10%), where most emissions occur in the electricity sector, as well as from chemical, rubber and plastic products and petroleum and coal products.

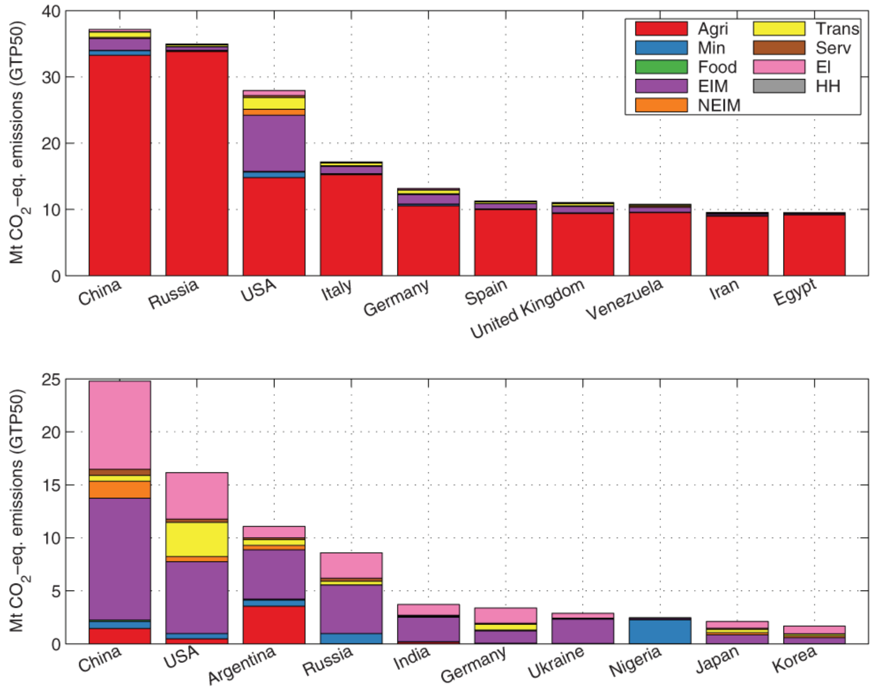

Figure 15: Top trading partners. Top figure shows exports from Brazil to other regions. Bottom figure shows imports from regions to Brazil. Note that emissions from LUC in other countries are not included.

Brazil is one example of the general trend of developing countries being net exporters of emissions, thus shifting the responsibility of global warming to developed countries when using a consumption approach (Peters et al., 2012b). This has been found to increase over time, whereas emission reductions are taking place in Annex I countries (due to the Kyoto Protocol) and production and emissions have been moved to countries with no commitment of reductions, the global emissions have steadily increased (Peters et al., 2011c). Similarly, production and exports of Brazilian beef and soybeans have increased over time (Paper 1).

Previous studies have estimated production emissions (Boden et al., 2013) and consumption emissions (Peters et al., 2011c) over time (Le Quéré et al., 2014). Figure 16 compares production and consumption-based emissions from the literature (excluding LUC emissions) with the results of Paper 1 (LUC emissions). As noted earlier, if emissions from LUC are excluded, the trade balance is close to zero. These apparent conflicting interests of increase production (which leads to emissions) along with increasing agricultural production and export shares, and greatly decreasing deforestation rates and emissions might suggest that either production or deforestation rates may change in the future.

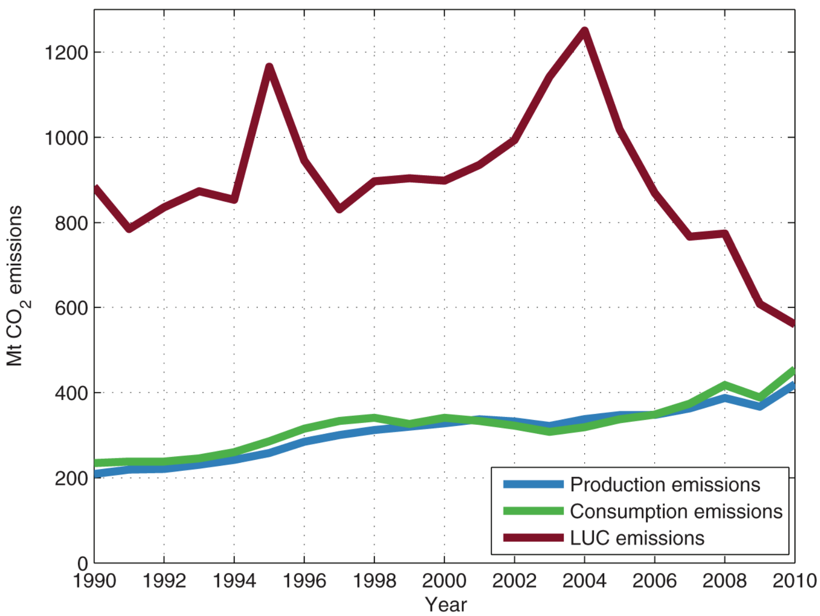

Figure 16: Brazilian production, consumption and LUC emissions over time. Production and consumption emissions do not include LUC emissions, and are from the literature (Boden et al., 2013, Peters et al., 2011c).

4.3. Uncertainties

Previous studies have found high uncertainties in non-CO_2 emissions from agriculture and deforestation, which is of particular importance in Brazil (IPCC, 2014b). Paper 4 found higher uncertainties in Brazil's production and consumption-based emissions than any other of the top 10 emitters (India is the only other country with roughly the same uncertainties). The main reasons for the high uncertainties are the large emissions of CH_4 and N_2O, which are considerably more uncertain than CO_2, due to the combined effects of emissions (tonnes) and climate response (temperature). While CO_2 was estimated to have an uncertainty (using AGTP50) of ±40%, CH_4 and N_2O were found to have ±70% and ±40% uncertainty, respectively. In this analysis, we use the relative metric (GTP50), to be consistent with the literature, thus CO_2 has no metric uncertainty, as $GTP_{CO2}=1$ (see Paper 4, Results section), and thus the uncertainties in the production and consumption-based emissions are a reflection of the non-CO_2 pollutants metric uncertainty and emissions uncertainty for all pollutants, in addition to uncertainty in economic data for the consumption-perspective.

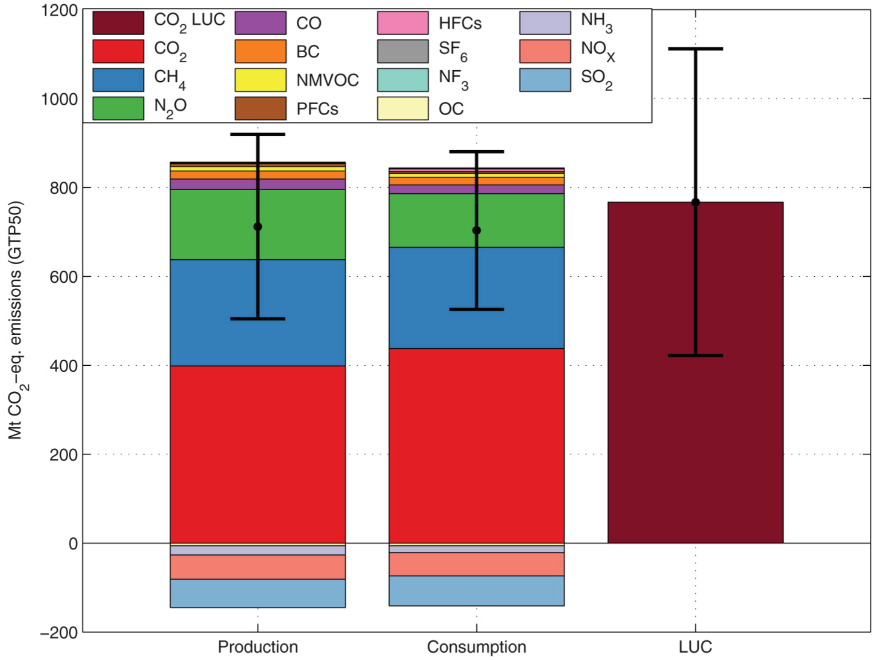

Figure 17: Production, consumption and LUC emissions, by pollutants, including uncertainties. Production and consumption emissions do not include LUC, in order to separate uncertainties. The black dot indicates net emissions, and the uncertainty ranges 95% confidence intervals.

Paper 4, using Monte Carlo analysis, found the Brazilian production emissions to have an uncertainty of ±30%, while the consumption-based emissions were within ±25%, using GTP50. Surprisingly, the consumption-based emissions have a lower uncertainty. The uncertainty difference between the two perspectives can be attributed to: (1) different mix of pollutants and (2) different distributions to sectors. The first can be seen in Figure 17, where CO_2 (having less uncertainty than other pollutants) has increased while the non-CO_2 emission have decreased, together slightly reducing total emissions and relative uncertainties.

The second is explained by the fact that emissions are much more evenly distributed among sectors in a consumption perspective than a production perspective, since production is specialized while consumption is smoothed by the global supply-chain (e.g. most production require electricity). This distribution difference has an effect on aggregated uncertainty, which can be tested with a simple RSS (root sum of squares) approximation (see discussion in Paper 4).

Paper 4 did not include emissions from deforestation, as is done in the previous section. This merging of emissions from deforestation adds additional uncertainties to the datasets from several sources: deforestation rates, carbon density in biomass and carbon cycle modelling. Very little explicit uncertainty information for regions exist, but comparisons of datasets and expert judgments suggests the absolute carbon emissions uncertainties in the last decades have been roughly the same (IPCC, 2014b). However, deforestation emissions have declined over the last decades, indicating that the relative error has gone up. Houghton et al (2012) estimated a global uncertainty of ±45%, which was based on four studies for the last decade, including expert judgments on data uncertainty and the incomplete understanding of the various processes (IPCC, 2014b).

Uncertainties in emissions from LUC are found to vary between continents, due to differences in carbon density variations, agricultural practices and monitoring capabilities (Baccini et al., 2012). Brazil has been the leading nation in country level monitoring and reporting of deforestation rates, using two satellite systems operated by INPE (Brazilian space agency). However, density in biomass is probably a large sources of uncertainty (one study said 60% of total uncertainty; (Houghton et al., 2000)), and the Amazon has a very large variance (Saatchi et al., 2007). Due to lack of regional information, it can be assumed that Brazil is comparable to the global average, thus the uncertainty in LUC emissions is estimates to be around ±45% (Figure 12). This is a crude assumption, and the uncertainty may even be higher. Combining uncertainties from LUC with production and consumption-based estimates using the RSS method, give 1480 ± 30% Mt CO_2-eq. emissions from production, and 1260 ± 30% Mt CO_2-eq. consumption-based emissions.

4.4. Policy context and outlook

Brazils emissions are large on a global scale, and emissions (excluding LUC emissions) continues to increase as emission grew annually at 2.5% from 2000 to 2010 (CAIT, 2014). The country has also seen rapid economic growth, from increasing production and increasing shares of beef and soy beans being exported over time. As discussed in Paper 1, this conflicting trend of protecting the rainforest by reducing deforestation rates, and increasing production and export shares of products that seem dependent on deforestation, may increase future deforestation due to economic interests. This scenario was partially confirmed by new estimates of deforestation rates (although not final estimates) by INPE, who found an increase between 2012 and 2013 of nearly 30%. This is especially problematic for countries investing in forest protection (such as Norway), and simultaneously consuming products from the region. Information campaigns and making consumers aware may reduce demand for products that cause large emissions. Although deforestation rates have decreased greatly since 2004, studies have found that increase in crop production without using new land may become increasingly difficult as current yield of e.g. soybeans in many places is very close to the climatic potential yield (Licker et al., 2010). Therefore, it seems that additional protective measures may be needed in the future in order to further protect the forests.

Brazil's emissions profile is clearly affected by international trade, and because of the large exports (which include emissions from LUC) it is a net exporter of emissions. The fact that other countries have made emission reduction commitments may have been beneficial to Brazil, since, as have occurred in many developing countries, manufactured products being exported to developed nations has driven much of the production increase. To reduce global emissions, climate policy must address emissions embodied in internationally traded products without introducing competitiveness concerns.

There are, however, several barriers to overcome in order to agree upon a single framework of emission calculations and allocations. The metric debate, ignited by Brazil due to their unusually high non-CO_2 agriculture emissions, is a hot political topic with large responsibility implications, as the comparisons of emissions are very sensitive to metric and parameters. Additionally, uncertainties in Brazilian emission estimates are high, especially due to highly uncertain pollutants. The inclusion of LUC adds additional layers of uncertainty, thus making the national estimates larger and potentially more uncertain.

Although trade has become an integral part of Brazil's emissions, most of the emissions occurring in Brazil are due to domestic demand, thus suggesting that strong domestic mitigation is needed. The challenge for Brazil is therefore to simultaneously tackle increasing demand, production and economic growth, and climate objectives. This can be turned into an opportunity for Brazil, due e.g. to its unique energy mix (Paper 2), further possibilities for intensification of agriculture, such as cattle ranching (Cohn et al., 2014), and continued monetary support for increased forest protection (Paper 1). With this, Brazil has an opportunity to spearhead the transition into a low-emissions economy.

5. Summary of papers

This section briefly explains the motivation and methods and lists the main findings in each paper.

5.1. Paper 1

Karstensen, J., Peters, G. P. & Andrew, R. M. 2013. Attribution of CO2 emissions from Brazilian deforestation to consumers between 1990 and 2010. *Environmental Research Letters*, 8, 024005.

Motivation and methods

Several countries, with Norway in the forefront, are spending large sums of money to help protect rainforests and reduce deforestation. Simultaneously, many countries are importing products from these countries and indirectly causing more deforestation. Our research connects these conflicting interests by looking into the question: w*hat are the consuming regions and sectors of CO_2 emissions embodied in products from Brazilian deforestation?*

We based our analysis on official deforestation estimates, coupled with a bookkeeping carbon-cycle model to estimate yearly emissions, taking into account the different agricultural practices in different Brazilian regions. We developed a time series from 1990 to 2010 of economic data, represented in a multi-regional input-output model. The emissions were connected to the economic model according to the estimated land-use transitions, and the emissions were finally allocated to final consumers in both sectors and regions.

Main findings

- Net CO_2 emissions from deforestation have increased from 880 Mt in 1990 to a peak in 2004 at 1250 Mt, and then decreased to 2010 at 560 Mt. The increase can be attributed to increasing agricultural production, while the sudden decrease is mostly a result of monitoring and law enforcements.
- Land-use transitions revealed that cattle ranching is the dominant land-use following deforestation, thus most emissions (71% in the last decade) were allocated to Brazilian beef production, and the rest (29%) to Brazilian soybean production.
- Most products produced on deforested land were consumed domestically over the period (85% of beef and 50% of soybeans), although the exported shares have increased over time.

- Asia has increased its import shares of both products, recently making it the dominant importer. The top importers of emissions embodied in beef in 1990 were the US and UK, while Russia has become the dominant importer in 2010. For soybeans, China remained the largest international consumer.

5.2. Paper 2

Lenzen, M., Schaeffer, R., **Karstensen, J.** & Peters, G. P. 2013. Drivers of change in Brazil's carbon dioxide emissions. *Climatic Change*, 121, 815-824.

Motivation and methods

Brazil is one of the most important emerging economies and may play a pivotal role in a future climate agreement. Brazil is a country with one of the least carbon-intensive energy supplies, due to renewable energy, but this is contrasted with large emissions from deforestation. This unique emissions profile may undergo changes in the near future as Brazil is transitioning into one of the world's largest economies. While deforestation rates have been decreasing, fossil-fuel based emissions are rising. For decision makers to develop policies to mitigate future emissions, we investigate the question: w*hat are the historical drivers of Brazils CO_2 emissions?*

We developed a time series of CO_2 emissions from deforestation, similar to Paper 1 but covering a larger time range. Additionally, estimates of CO_2 emissions from energy use were created from national data, and all emissions were mapped to their respective sectors in monetary (supply-use) tables. A specific input-output technique (structural path decomposition) was used to find the underlying drivers of annual changes to historic emissions. The main contribution from this thesis is the development and analysis of the deforestation results.

Main findings

- CO_2 emissions from deforestation clearly dominates historic emissions, and has been driven, at the production side, mainly by increasing economic demand per capita, increasing population and decreasing by changing demand. Emission intensities (CO_2 per R$ output) saw a large increase in the 70s and 80s (due primarily to large deforestation rates, but also affected by “spin-up” of the deforestation emissions in the model) and decrease in the last decade (due mainly to law enforcements). On the consumption side, the same emissions are mostly driven by manufactured products (including food), with beef consumption dominating the historic changes to emissions.

- CO_2 emissions from energy supply have mainly been driven by the same factors, apart from compensating effects from improved emission intensity.
- Overall, per-capita consumption has been the largest driver of increasing emissions in recent years, counteracted mainly by decreasing emission intensities. The drivers points to different policy options in terms of mitigation.

5.3. Paper 3

Karstensen, J., Peters, G. P. & Andrew, R. M. 2014. The temperature response to the current consumption of goods and services. *Climatic Change (in review).*

Motivation and summary

The emissions associated with the consumption of goods and services have generally increased in developed countries (relative to territorial emissions), as they increasingly import products with the resulting emissions occurring in the country of production (emissions embodied in traded products). Most of these analyses have focused on CO_2 only, or long-lived GHGs using a Global Warming Potential. Recently, climate policy has become framed around the 2°C target, making regional and sectoral temperature contributions highly relevant, as different allocations may affect mitigation strategies. We explore how future temperature change can be allocated to consumers: *What are the current regional and sectoral producers and consumers of global temperature change?*

We combine multi-pollutant emission statistics with the Global Temperature change Potential metric, to convert emissions to temperature change. The temperature response is allocated to producers and consumers in sectors and regions using a multi-regional input-output model for the year 2007. Although the focus in on a 50 year time horizon, annual temperature response from 1 to 100 years were explored to assess how sector and region contributions change with the time horizon.

Main findings

- Globally, the temperature response of production suggests China is the largest emitter (GTP50), while consumption-based emissions suggest USA is the most important driver. Sectoral emissions from production occur mostly in electricity, energy intensive manufacturing and agricultural sectors, while consumption shifts emissions to secondary and tertiary sectors such as service, non-energy intensive manufacturing and food sectors.
- International trade can be attributed nearly a quarter of global emissions, with China dominating emissions in exports and USA and EU27 dominating imports.
- The inclusion of SLCFs and long-lived GHGs not part of the Kyoto Protocol substantially changes the net sectoral effects, especially due to cooling pollutants like SO_2 and NO_X.
- The GTP50 finds different sector attributions than GWP100, due mainly to less weight on cooling and warming SLCFs. Temporal changes along time horizons of the metric also change the importance of sectors.

5.4. Paper 4

Karstensen, J., Peters, G. P. & Andrew, R. M. 2014. Uncertainty in temperature response of current consumption-based emissions estimates. *Earth System Dynamics (submitted).*

Motivation and summary

The attribution of multi-pollutant emissions and temperature response to producers and consumers can help explore mitigation options in an effort to keep global warming below 2°C. However, such an analysis relies on datasets, methods and assumptions that include uncertainties, sometimes considerable. We explore uncertainty from the point of consumption through to the temperature response to reveal: *How uncertain are consumption-based emissions and the corresponding temperature change?*

Our analysis focusses on parametric uncertainties, and we draw on the literature to estimate the uncertainties in emission statistics and economic datasets, and establish an inverse relationship between relative uncertainty and sector sizes, and use this relationship to estimate uncertainties at the sectoral and regional level where uncertainty data is generally non-available. Uncertainties in climate parameters used in emission metrics are taken from the literature. The emissions are converted to global temperature change using GTP. We perturb all parameters using Monte Carlo analysis and measuring the spread on the end results, with a separate focus on economic data, emission statistics, and metric values, before doing a complete propagation of uncertainty over the complete cause-effect chain.

Main findings

- Sectors and regions with large emissions of SLCFs generally exhibit higher uncertainties as the relationships between activities and emissions are uncertain.
- The relative metric GTP has much lower uncertainties than the absolute metric AGTP, as it is normalized by CO_2 and thus removing some of the effect of the uncertain climate response (which usually dominates the metric uncertainties). A time horizon of 50 years generally shows lower uncertainties than 100 years.
- Consumption-based emissions are found not to be substantially more uncertain than production emissions, due to low uncertainties in economic data and cancellation of errors in the input-output calculations. Uncertainties for regions and global sectors do change between the two perspectives however, due mainly to different allocations of pollutants and distributions over sectors.
- Aggregation of regions and sectors changes the uncertainties as errors tend to cancel via aggregation.
- While uncertainties in metric values dominate in global sectors, emission uncertainties may be more important at national level. Economic uncertainties are low, but remain unreliable.

6. Conclusions and outlook

With global CO_2 emissions increasing at more than 3%/year and temperature scenarios indicating dangerous global warming of more than 2°C by around 2060, there is a need for addressing current production and consumption that is leading to future temperature change. The studies presented in this thesis combine the concepts of sectoral and regional contributions of emissions and temperature change through production and consumption in order to find the underlying drivers of climate change, and through this eventually lead to more robust suggestions to policy makers seeking to mitigate GHG emissions.

The main findings of the studies presented support the hypothesis of consumption being a driver of emissions. Paper 1 quantifies the regional and sectoral consumption CO_2 emissions embodied in products from Brazilian deforestation. Domestic consumption was found to dominate, by being responsible for 70% of the emissions in the last decade, where most was due to beef consumption. As the global community is using monetary transfers to protect the Amazon rainforest, they are simultaneously consuming products that are dependent on deforestation, and thus driving ~30% of the deforestation and emission happening in the Amazon. Although the study found that deforestation emissions decreased from the 2004 peak, production and exports of beef and soybeans have increased, thus trade has increasingly been driving emissions from deforestation. These conflicting interests (reducing deforestation and increasing production) may result in future increased deforestation rates. After the study was published, INPE published early deforestation estimates for 2013 indicated a nearly 30% increase in deforested area compared to 2012 (INPE, 2012). With detailed analysis of the underlying drivers of production leading to emissions from deforestation, it may be possible to create climate policies specifically targeting consumption potentially linked to deforestation.

Paper 2 found the historical increases of Brazils CO_2 emissions to be mostly driven by increasing emissions intensity (emissions per R$, when including land-use change), population growth and increasing per-capita consumption. Mitigation can therefore consider supply-side management, such as agricultural intensification of cattle grazing, and demand-side management, such as influencing consumer demand.

Paper 3 estimated the current regional and sectoral producers and consumers of global temperature change. Large redistributions of emissions at the sector and region level were seen when changing between the allocation perspectives. Additionally, the inclusion of non-Kyoto pollutants with warming and cooling effects has substantial effects on the sectoral impact on global temperature, and the results are highly dependent on parameters and methods, as e.g. a change in metric time horizon can change sectors importance, thus they should be considered carefully. This work shows that a significant part of global emissions and temperature change can be attributed to international trade. Consequently, emission mitigation strategies should optimally include this to avoid leakage.

Paper 4 explored the uncertainties of emissions data, metric parameters and economic data, to estimate the uncertainties in consumption-based emissions and temperature change. The study found the uncertainties in the results to be highly dependent on data aggregations and method choices. Uncertainties in the economic data were in most cases negligible, but may be higher if structural uncertainties are included. At the national level, the emissions and metric uncertainties are dominating different regions respectively, while economic data is negligible among the large countries. Sectoral levels reveal much higher uncertainties, and can even be dominated by economic uncertainties. The analysis shows that the consumption-based emissions are not substantially more uncertain than the territorial-based emissions on a national level. With uncertainties on regional and sectoral emissions overlapping, the results suggest that the ordering of countries and sectors by production and consumption-based emissions may be uncertain. This work points to research areas where uncertainties should be reduced in order to more accurately understand the consequences of production and consumption.

These studies have also identified several important research gaps: such as (1) the need for consumption-based deforestation emissions in other regions, such as central Africa and south-east Asia, (2) the possibility of increased agricultural production in Brazil without the need for additional deforestation, (3) the understanding of how evolving trade patterns change regional emissions over time, (4) increased understanding of the climate response to emissions and (5) thorough analysis of uncertainties in economic data and structural uncertainties in MRIO models. Further research on these topics is needed in order to fully understand the consequences of possible mitigation options. The analysis in this thesis has not touched on adaptation, but as the effects from climate change (droughts, flooding, etc.) are likely to happen more frequently in the near future, a key gap in the literature is how complex supply-chains linking production, trade and consumption may change and be impacted due to e.g. changing agricultural potential, changing economic wealth and impacts of climate change.

Together, the studies presented here have contributed to the literature by showing the driving forces behind recent emissions leading to climate change, and their estimated uncertainties. With this information available, cost-effective climate policies can be shaped based on the understanding of the extended cause-effect chain, so that conflicting interests can be revealed and policies can hopefully become effective in avoiding dangerous climate change.

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Attribution of CO_2 emissions from Brazilian deforestation to consumers between 1990 and 2010

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Abstract
Efforts to reduce deforestation to mitigate climate change and to conserve biodiversity are taking place on a global scale. While many studies have estimated the emissions occurring from deforestation, few studies have quantified the domestic and international drivers sustaining deforestation rates. In this study we establish the link between Brazilian deforestation and production of cattle and soybeans, and allocate emissions between 1990 and 2010 along the global supply chain to the countries that consume products dependent on Brazilian deforestation. We find that 30% of the carbon emissions associated with deforestation were exported from Brazil in the last decade, of which 29% were due to soybean production and 71% cattle ranching. The share exported is growing, with industrialized nations and emerging markets (especially Russia and China) greatly increasing imports. We find a correlation between exports (and hence global consumption) of Brazilian cattle and soybeans and emissions from deforestation. We conclude that trade is emerging as a key driver of deforestation in Brazil, and this may indirectly contribute to loss of the forests that industrialized countries are seeking to protect through international agreements.

Keywords: deforestation, CO_2 emissions, trade, consumption, consumers, Brazil, Amazon, input–output analysis, land-use change

1. Introduction

Global CO_2 emissions rose nearly 50% over the last two decades (Peters *et al* 2012b), and estimates suggest land-use change (LUC) was one of the largest individual sources, contributing approximately 15% between 1990 and 2010 (Peters *et al* 2012b, Houghton 2012). High emissions from LUC mostly occur in the tropical regions, where forest carbon density is highest (Baccini *et al* 2012). Forest loss releases carbon stored in biomass and soil to the atmosphere, increasing radiative forcing and temperature changes on a global scale (Bala *et al* 2007). Reducing tropical deforestation is desirable, not only because it might be one of the cheapest options to effectively reduce global CO_2 emissions (Kindermann *et al* 2008), but also because it would enhance sinks and protect valuable ecosystems (Canadell and Raupach 2008). Between 1970 and 2010, approximately 18% of the Brazilian Amazon was deforested (Baccini *et al* 2012), with the primary cause being demand for new land for the cultivation of soybeans and expansion of pasture (Barona *et al* 2010, Hosonuma *et al* 2012).

The REDD+ initiative (Reducing Emissions from Deforestation and forest Degradation) is creating incentives for developing countries with large deforestation rates to reduce forest loss and encourage regrowth. However, as industrialized countries are paying to protect tropical forests through mechanisms such as REDD+, the same countries

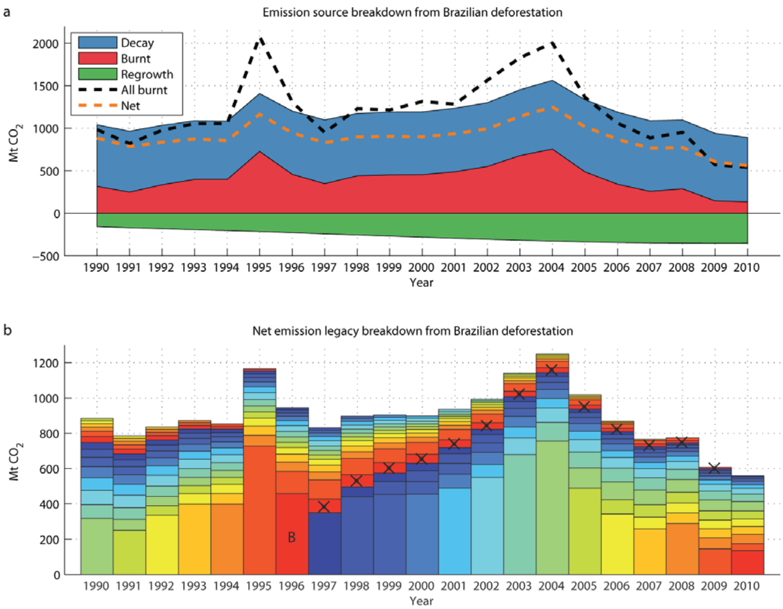

Figure 1. Estimated emissions from Brazilian deforestation, 1990–2010. (a) Estimated burnt and legacy (decay) emission components, and emission absorption from regrowth. The 'all burnt' line is a theoretical scenario where we assume that all deforestation is burnt in the year it was cut down, calculated as deforestation area multiplied by carbon density in biomass per area (by state). We use net emissions (burnt plus legacy less regrowth) in our analysis, divided into year-by-year components. (b) In each year, the component of the vertical bar closest to the horizontal axis represents emissions from deforestation in that year, while legacy emissions from that year's deforestation propagate into later years, represented with the same component color. For example, a part of the forest cleared in 1996 was burnt (the red component in 1996 marked with a 'B'), while the unburnt residual decayed over time (legacy emissions: red components from 1997 to 2009, marked with crosses).

might also indirectly be driving deforestation via consumption of agricultural products from the very countries whose forests they aim to protect (Pacheco *et al* 2010). To uncover these linkages, a model of the global supply chain is necessary to estimate the consumption of goods and services associated with agricultural commodities produced on deforested land in Brazil. Linking deforestation and its associated emissions to agricultural production and international trade can reveal the global socio-economic drivers leading to domestic and international production and consumption.

In recent years, consumer approaches to emission inventories have been emerging, shedding light on the links between geographically separated production and consumption (Davis and Caldeira 2010). In a consumer approach, a proportion of the territorial emissions occurring in producing countries are reallocated from producing to consuming nations (Peters *et al* 2011b). While several ways of sharing allocation among producers and consumers have been explored (Andrew and Forgie 2008, Lenzen *et al* 2007, Zaks *et al* 2009), this study follows the approach of most studies by assuming full allocation to the final consumer. In this view, the consumer is at the end of the global supply chain, creating demand and sustaining/increasing production and international trade of goods and services, leading in turn to deforestation and emissions. Recent studies have shown that a significant share of global CO_2 emissions are embodied in international trade (Peters *et al* 2011b), making consumer approaches increasingly relevant. While there has not yet been a thorough analysis of CO_2 emissions from LUC embodied in international trade, earlier work has indicated the importance of regional forces (Aguiar *et al* 2007) and international trade and consumption (DeFries *et al* 2010, Zaks *et al* 2009) in driving deforestation.

2. Methods

In our analysis we link current and legacy emissions (Ramankutty *et al* 2007) to a detailed model of the global economy for the years 1990–2010 (Peters *et al* 2011b) to quantify the relationship between global consumption and emissions from Brazil's deforestation. Using areas of deforestation estimated in the PRODES project database by the Brazilian National Institute for Space Research (INPE 2012), we estimate continuous net emissions (figure 1(a)). The land-use change and carbon cycle modeling follow Ramankutty *et al* (2007), with updated carbon stock and land-use estimates according to Zaks *et al* (2009) and Galford *et al* (2010).

All model runs over all years were done for each Brazilian state separately, with state-specific carbon density in aboveground biomass, burnt/legacy emission shares, and soybean/cattle land-use shares. State average aboveground live biomass ranges from 95 to 270 Mg ha^{-1} (Saatchi *et al* 2007). The deforested biomass is partitioned into shares with different decay rates: burnt (20% share), slash (70%), products (8%) and elemental carbon (2%) (Zaks *et al* 2009). In the state of Mato Grosso the burnt (70%) and slash (20%) shares are different due to different agricultural practices (Galford *et al* 2010). With only the burnt share releasing emissions the same year the deforestation is occurring, most emissions will usually occur in later years (legacy emissions). Legacy emissions were included from 1977, being INPE's first estimate of deforestation (INPE 2012), resulting in each year having a current emission component and a legacy emission component (figure 1(b)). With this methodology, carbon emissions are allocated when there is a flux from cleared biomass to the atmosphere.

The share of land-use in the year of deforestation in most states is 34.7% for cropland and 65.3% for pastures. This ratio is modeled and found to change over the following years, to be dominated by pastures and secondary forest (regrowth). The emissions are allocated to products from cropland (soybeans) and pasture (cattle meat) according to the land-use following deforestation (Barona *et al* 2010, Fearnside 1996, Galford *et al* 2010, Ramankutty *et al* 2007). Again, shares for Mato Grosso are different: initial share of 65% for cropland and 35% for pastures (Morton *et al* 2006, DeFries *et al* 2010).

Our attribution analysis starts in 1990 and this allows the legacy emissions to accumulate for 13 years (1977–1989) before the analysis begins. For consistency, and with only very minor effects, we therefore only consider legacy emissions for 13 years starting in each year of deforestation. Even though deforestation rates have seen a rapid decline in recent years, probably as a result of strict policy enforcements (Malingreau *et al* 2012), legacy emissions (from gradual decay of wood products and clearance waste) partly sustain emissions over time, creating inertia in the emission trajectories (Aguiar *et al* 2012). Even so, both deforestation rates and net emissions are lower now than at any time in the last 21 years, with 560 $MtCO_2$ estimated in 2010 compared with the 1990–2010 average of nearly 900 $MtCO_2$ (figure 1).

This study does not consider indirect land-use change (e.g. indirect land-use change impacts of biofuels), and only allocates emissions to the primary direct drivers, i.e. cultivation of soybeans and grazing of cattle, according to the literature (Barona *et al* 2010, Houghton 2012, Fearnside 1996).

Each year's emission estimates (both current and legacy emission components) were divided among Brazil and countries importing meat and soybeans according to supply chain shares. The supply chain is modeled using Multi-Regional Input–Output (MRIO) analysis derived from data from the Global Trade Analysis Project (GTAP) (Peters *et al* 2011a, Narayanan *et al* 2012), a database which contains global bilateral trade information for 129 regions and 57 sectors for specific years. Bilateral trade data links the regions at the sector level and additionally separates between intermediate and final consumption (Peters *et al* 2011a). Using 1997, 2001, 2004 and 2007 as base years, we created a full time-series with trade (TSTRD) from 1990 to 2010 based on gross-domestic product (GDP), bilateral trade and emission statistics (Peters *et al* 2011b).

The base years cover different time periods in the TSTRD: 1990–1998 (1997 base year), 1999–2002 (2001 base year), 2003–2005 (2004 base year) and 2006–2010 (2007 base year). Due to issues with the share of consumption in households compared to exports in the 1997 dataset, we excluded it in the analysis of beef. The 1997 version of Brazil's economic structural data in GTAP is based on data from 1985, and shows that a very high share of final consumption going to households compared to the other reference years, which is not consistent with more recent Brazilian data. Because of this, we use the 2001 dataset as a base for the years back to 1990 for calculations relating to beef. The base years are detailed and accurate representations of the global economy, and while the interpolated time-series is less accurate than the data for individual base years, it allows the robust assessment of trends (Peters *et al* 2011b). The MRIO model has a high level of detail on agricultural and food products, and we assume that in Brazil the sector 'Oil seeds' is mostly soybeans, and 'Bovine cattle, sheep and goats, horses' is mostly cattle, which is a reasonable assumption in a Brazilian context.

Using the time-series, we allocate legacy emissions differently based on a trade matrix of the year the legacy emissions belong to. The emissions are allocated to the consuming countries in the year the emissions occur, which in the case of legacy emissions is later than the year of consumption that led to deforestation (figure 1(b)). For legacy emissions connected to a year before 1990 (legacy emissions in 1990–2002), we assumed trade shares equal to those in 1990. The model allocates deforestation emissions to all products of the beef and soybean sectors regardless of whether they were produced on newly deforested land or existing land (which suggests that consumers do not know the source of production). This can be justified since most soybean production and cattle ranching in Brazil occurs on newly or previously deforested land (Barona *et al* 2010).

3. Results

Including the entire supply chain, Brazilian consumption has led to the largest share of emissions from its own deforestation: on average over the two decades, 85% of the emissions embodied in Brazilian beef products and 50% of Brazilian soybean products have been driven by domestic consumption. Due to the rapid growth in international trade in recent decades, Brazilian shares of these emissions are generally decreasing over time. The exported CO_2 emissions from all Brazilian deforestation over 1990–2010 averaged 25% (with a minimum of 18% in 1990, and a maximum of 37% in 2004). For beef products the average exported was 15% (ranging from 12% in 1998 to 19% in 2008), while for soybean products the average exported was 50% (ranging from 33% in 1996 to 69% in 2004) (figure 2).

Particularly in the last decade, greater imports by emerging markets and industrialized countries have led to an increasing share of the exported emissions (figure 3). While

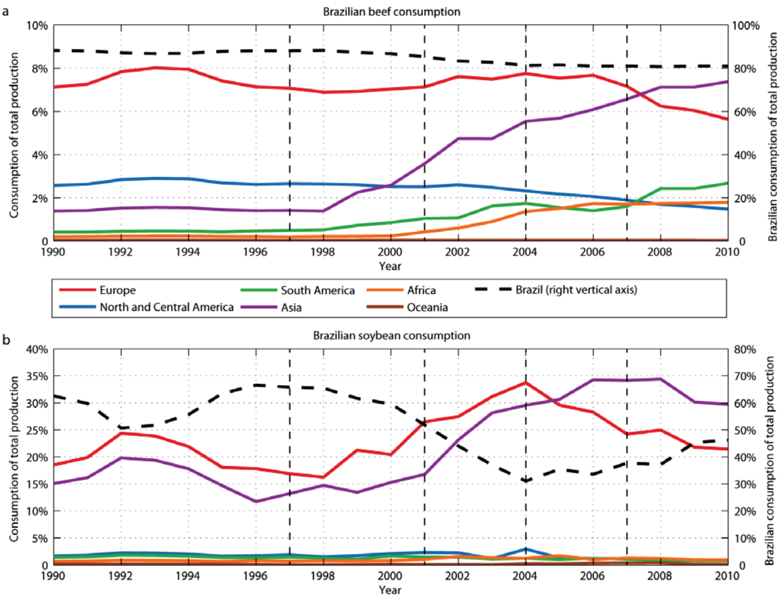

Figure 2. Export shares of Brazilian (a) beef and (b) soybeans to regions. The share of emissions linked to beef that was exported to Europe has fallen slightly, while Asian consumption (driven mainly by Russia) has been steadily rising over the last decade. A similar development can be seen in emissions linked to soybean production exported to the European and Asian markets. According to our estimates, Asia (mainly due to China) now consumes more than the European market. Brazil's meat consumption (right vertical axis) has seen a more steady development than soybean consumption, while being the dominant consumer of both products. Vertical dashed lines indicate the base years of our analysis (see section 2).

the largest share of exported emissions from Brazilian beef production in 1990 were embodied in trade to the USA and the UK, Russia has recently increased its share from very low levels to becoming the world's largest importer of emissions embodied in Brazilian beef in 2010 (from 0.1% of production in 2000, to 2.8% in 2010), with 15% of total exported beef. China's share of emissions linked to soybeans has increased from 7% of total production emissions in 2000 to 22% in 2010, equivalent to about 41% of the emissions embodied in exported soybeans in 2010. While consumption by most regions has been very stable over the last two decades, the Asian and European markets have seen large changes. Our study indicates that the Asian market now has a larger share of beef and soybean emissions than the European market (figure 2): Asia is now allocated 7% of total beef emissions (driven mainly by Russia and the Middle East) and 30% of total soybean emissions (driven mainly by China).

The increase of emissions from 1998 to 2004 (355 $MtCO_2$) coincided with the growth of the total exported share from 18% to 37%. So while domestic consumption grew slightly from 730 to 790 $MtCO_2$, exports almost tripled, growing from 165 to 460 $MtCO_2$. Due to the large inter-annual variability of the deforestation rates, the share exported is a better metric to portray the drivers of deforestation. Our analysis suggests that, in recent years, there is a positive correlation between high deforestation emissions and high proportions of production exported, giving additional support to the hypothesis that deforestation is increasingly connected to international trade (DeFries *et al* 2010). We split the analysis into multiple time periods as these time periods cover different data sources, and while there is no apparent correlation in the first time periods between emissions from deforestation and the share of the emissions exported, there is correlation in the later time periods (figure 4). Although we find a correlation between emissions from deforestation and export share, we do not attempt to isolate the direction of the causation, which would require different analytical approaches.

Assuming causation in one direction would mean that increases in the share exported would lead to increased deforestation rates and growth in emissions. For example, following the trends from 2003 to 2010, if the export share of soybeans were to increase by 10 percentage points (e.g. from 60% to 70%), the deforestation emissions would be expected to rise by about 160 $MtCO_2\ yr^{-1}$. Similarly, if the export share of beef were to increase by 10 percentage points (e.g. from 20% to 30%), the emissions from deforestation would be expected to rise by 480 $MtCO_2\ yr^{-1}$. Causation in this direction implies deforestation is driven by market demand.

In contrast, if one views the causation in the opposite direction, then if emissions from deforestation due to soybeans were to increase by 100 $MtCO_2\ yr^{-1}$, the export share of soybeans would be expected to increase by 6 percentage points (e.g. from 60% to 66%). For emissions related to beef, an increase of 100 $MtCO_2\ yr^{-1}$ would lead to an increase of the share exported by 2 percentage points

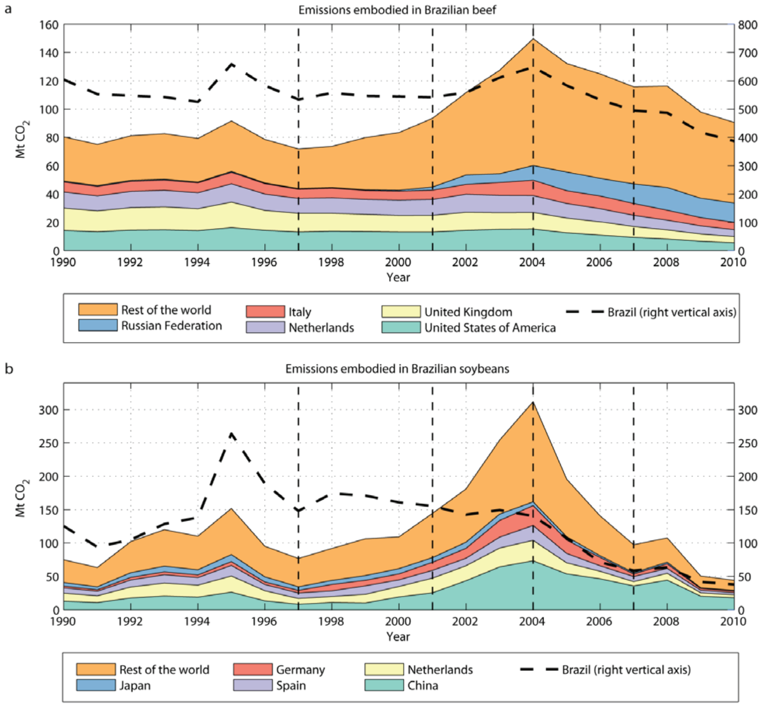

Figure 3. Deforestation emissions in trade distributed among top importers of (a) beef and (b) soybeans from 1990 to 2010. In total, Brazil (right vertical axis) is responsible for about 85% of the emissions from cattle, and 50% of the emissions from soybeans. Deforestation rates do have an important impact on the emissions embodied in trade, as low deforestation rates imply less emissions allocated to consumption. However, legacy emissions and high export shares counter that trend. Vertical dashed lines indicate the base years of our analysis (see section 2).

(e.g. from 20% to 22%). Causation in this direction implies deforestation and increased cultivation occur first and markets are then found for new production.

4. Discussion and conclusion

There are large uncertainties in current LUC emissions estimates, and the estimates are strongly affected by parameter choices (Ramankutty *et al* 2007, Aguiar *et al* 2012). Many of the parameters are hard to constrain due to lack of data, suggesting that the share of emissions allocated to particular economic sectors is uncertain. To reduce uncertainty we have used recent land-use transition data (Galford *et al* 2010, Zaks *et al* 2009) and INPE's updated dataset from 1977 to 2010, consistently used legacy emissions for all years in the analysis, and allocated legacy emissions to the year the legacy emissions are released and according to the trade shares from the year the deforestation originates.

Global economic and trade data come with uncertainties as they require the merging and harmonization of conflicting datasets (Lenzen *et al* 2012a). While the uncertainty of the data is difficult to estimate, previous authors have found the robustness of consumption-based estimates to be relatively high, as the uncertain data tend to be small and generally uncorrelated errors in individual data points tend to cancel (Peters *et al* 2012a, Lenzen *et al* 2010, Lenzen 2011, Peters *et al* 2011b). Thus, the long-term trends of regions are considered more accurate representations of the global situation than specific data points.

Trade is emerging as a key driver of agricultural expansion and therefore deforestation in Brazil, with two key implications. First, consumption of Brazilian soybeans and beef by countries who are already seeking to protect Brazilian forests (e.g., via REDD+), are driving demand and therefore indirectly increasing the deforestation they are seeking to prevent. With these indirect links quantified, measures can be taken in the consuming countries to limit the pressure on Brazil's forests using, for example, policies to influence consumption patterns or regulation of products originating from deforested land. Second, the recent land-use change trend in Brazil might not continue, as production (FAO 2012) and export shares have largely been increasing while deforestation rates have seen a dramatic decrease over recent years (figure 4). With increasing global pressure on Brazilian agriculture to increase production (Nassar 2009), desire for continued economic growth, and emerging changes to the Brazilian Forest Code (Tollefson 2012), it appears unlikely that Brazilian deforestation rates will continue to decrease

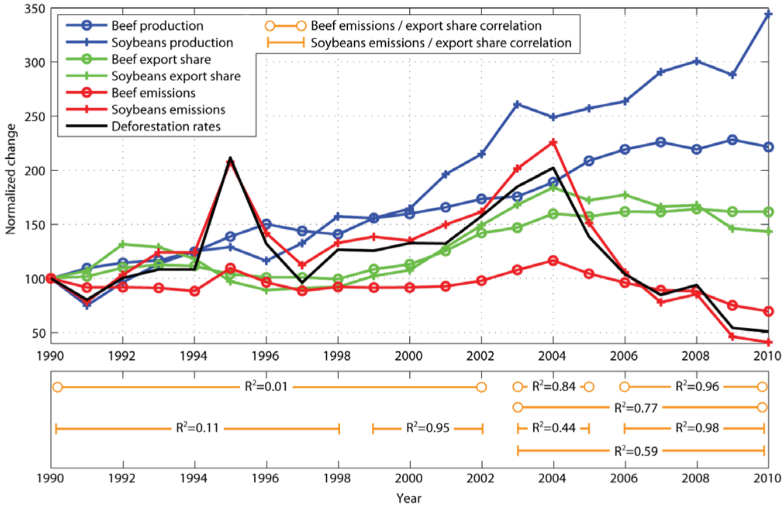

Figure 4. Changes to production, trade shares, emissions and deforestation rates (normalized to 100 in 1990), and R^2 values from correlation of emissions linked to beef and soybeans and export shares of production. Production (FAO 2012) and export shares of beef and soybeans have increased over 21 years, while value added from the agriculture sector in Brazil has doubled (measured in constant 2000 US$) (World Bank 2012). Emissions linked to soybeans follow deforestation rates more closely than emissions linked to beef due to different land-use transitions (Ramankutty *et al* 2007), however, both deforestation rates and emissions have decreased since 2004. Because of these recent contrasting trends, the development of deforestation rates or production of agricultural products may change. To sustain the increasing demand for products (and the economic growth that it brings), it is likely that land-use expansion will continue (Malingreau *et al* 2012). The R^2 values show increasing correlations between emissions and export shares from 1990 to 2010, implying a connection between deforestation and global trade in recent years. To show how the correlations change over time, we do the regressions on the time periods based on when different base years are used in the time-series (see section 2), in addition to a correlation between 2003 and 2010.

at the current rate without strengthening measures to protect forests (Malingreau *et al* 2012).

To sustain and increase the current level of production and exports, Brazil would need to either intensify agricultural production or use more land (which may lead to additional deforestation). Agriculture in Brazil has seen a dramatic increase in productivity since 1960 (155% for cattle and 300% for cropland), but the projections for the next decade show much lower expected gains (24% for cattle and 23% for cropland, from 2010 levels to 2021) (Mapa a, Mapa b). The hypothesis that deforestation rates might rise is strengthened by a recent study concluding that the current yield of soybeans in Brazil is in most places very close to the climatic potential yield, indicating low potential for further increase in agriculture production without the use of additional land (Licker *et al* 2010). Another study suggests that, in the event that deforestation rates level out, emissions will remain high as loggers move into more dense forests, where carbon density is higher (Loarie *et al* 2009).

Our analysis suggests that Brazil's deforestation cannot be considered in isolation from the global supply chain. Similar conclusions have recently been highlighted for the rapid growth of CO_2 emissions in emerging economies (Peters *et al* 2011b), for global biodiversity loss (Lenzen *et al* 2012b) and water consumption (Hoekstra and Mekonnen 2012). Since global drivers contribute to Brazil's deforestation, they should also be seen as a part of the solution. A first step in this direction is a full assessment of the consumption patterns that indirectly lead to deforestation and agricultural expansion, building on studies such as this analysis. The complexity of the global supply chain in transforming agricultural output into everyday commodities may make regulation difficult, suggesting regulation is required at several points in the supply chain. Examples of potential regulation points are deforestation itself (e.g., REDD+), importers of agricultural commodities, and consumers who have the ability to change behavior away from particular products (e.g., via labeling or information campaigns). Such distributed regulation can facilitate the use of a wide range of complementary mitigation policies and measures, potentially increasing effectiveness.

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Uncertainty in temperature response of current consumption-based emissions estimates

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Abstract

Several studies have connected emissions of greenhouse gases to economic and trade data to quantify the causal chain from consumption to emissions and climate change. These studies usually combine data and models originating from different sources, making it difficult to estimate uncertainties in the end results. We estimate uncertainties in economic data, multi-pollutant emission statistics and metric parameters, and use Monte Carlo analysis to quantify contributions to uncertainty and to determine how uncertainty propagates to estimates of global temperature change from regional and sectoral territorial- and consumption-based emissions for the year 2007. We find that the uncertainties are sensitive to the emission allocations, mix of pollutants included, the metric and its time horizon, and the level of aggregation of the results. Uncertainties in the final results are largely dominated by the climate sensitivity and the parameters associated with the warming effects of CO_2. The economic data have a relatively small impact on uncertainty at the global and national level, while much higher uncertainties are found at the sectoral level. Our results suggest that consumption-based national emissions are not significantly more uncertain than the corresponding production based emissions, since the largest uncertainties are due to metric and emissions which affect both perspectives equally. The two perspectives exhibit different sectoral uncertainties, due to changes of pollutant compositions. We find global sectoral consumption uncertainties in the range of ±9–±27 % using the global temperature potential with a 50 year time horizon, with metric uncertainties dominating. National level uncertainties are similar in both perspectives due to the dominance of CO_2 over other pollutants. The consumption emissions of the top 10 emitting regions have a broad uncertainty range of ±9–±25 %, with metric and emissions uncertainties contributing similarly. The Absolute global temperature potential with a 50 year time horizon has much higher uncertainties, with considerable uncertainty overlap for regions and sectors, indicating that the ranking of countries is uncertain.

1 Introduction

Many studies have shown that national greenhouse gas (GHG) emission accounts can be viewed from either a production (territorial) or consumption perspective (Davis and Caldeira, 2010; Hertwich and Peters, 2009; Wiedmann, 2009; Peters and Hertwich, 2008). While the production view only looks at territorial emissions, the consumption view includes emissions from the production of imported products and excludes emissions from the production of exports. It has been shown that territorial emissions have decreased in most developed countries since 1990, but consumption-based emissions have increased (Peters et al., 2011c). This indicates that growth in consumption and international trade may undermine the effectiveness of climate policies that only limit emissions in a subset of countries, such as in the Kyoto Protocol (Wiebe et al., 2012; Kanemoto et al., 2013).

The concept of consumption-based emissions estimates can therefore be used to extend the cause-effect chain from consumption, to production, to emissions, and ultimately to global warming (Fig. 1). This is an important complement to the established territorial (Kyoto Protocol) viewpoint, particularly to link more directly to consumption as a key driver of emissions. More recent studies have broadened this concept to look at further consequences of increased global demand for traded products, such as deforestation (Karstensen et al., 2013), biodiversity loss (Lenzen et al., 2012), dependency on traded fossil fuels (Andrew et al., 2013), land-use change (Weinzettel et al., 2013), and water footprints (Hoekstra and Mekonnen, 2012).

In the estimation of consumption-based emissions accounts, various datasets and models are combined in the calculations, thus uncertainties and errors may arise in a number of datasets and models: emission data, metric data, economic data, etc. There are also uncertainties in assumptions and study design that can be more difficult to explicitly quantify, including which metric and time horizon to use for comparing pollutants, and how economic data for one specific year can be relevant to other years.

The uncertainty of many aspects of the cause-effect chain have been investigated previously (Höhne et al., 2011; Prather et al., 2012), but the link to consumption has not been made. There is a growing literature on the uncertainty in input-output (IO; economic) models used to estimate consumption-based emissions (Wilting, 2012; Lenzen et al., 2010; Peters et al., 2012), but this literature is still not sufficiently robust and large knowledge gaps remains (IPCC, 2014). A number of studies have investigated uncertainty in emissions (European Commission, 2011; UNEP, 2012; Marland et al., 2009; Macknick, 2011), both regional and global, but surprisingly there still does not exist an emission dataset with specified uncertainties at the country level across all climate-relevant species. In addition, there exist almost no estimates of uncertainty at the sector level. Many aspects of uncertainty have been investigated in the climate system (Skeie et al., 2013; Prather et al., 2012; Myhre et al., 2013b), but there is little literature on the uncertainties in emissions metrics (Olivié and Peters, 2013; Shine et al., 2007; Reisinger et al., 2010). We are not aware of any studies that have estimated the uncertainty introduced by each model and dataset (e.g. metric and IO uncertainties), or how uncertainty propagates when estimating climate change from consumption as a socio-economic driver.

We extend the uncertainty analyses done by Prather et al. (2009), Höhne et al. (2011) and den Elzen et al. (2005) by including consumption-based emissions for a single year and using a temperature-based emission metric, which is arguably a more policy-relevant method of weighting emissions. We use Monte-Carlo analysis and draw on previous studies of uncertainties to perturb and highlight the different contributors: economic data, emission and metric parameters, and then compare our results with the previous studies.

2 Methods

We consider the propagation of uncertainty from the point of consumption of goods and services (products), to the production of products where emissions to air occur, to the climate impacts caused by those emissions (Fig. 1). This can be thought of as a causal chain where consumption is assumed to be the primary driver, in turn driving production, which in turn leads to emissions, and then emissions lead to temperature change. These components of the cause-effect chain are linked by calculation methodologies, each requiring parameterization, and we break the analysis into those three components: economic data, emission statistics, and emission metrics. We estimate the uncertainty for each of the components individually, and finally connect the components to determine how uncertainty propagates through the cause-effect chain.

To determine the temperature response to a given level of consumption, we first map emission statistics for most important pollutants to producing regions and sectors (European Commission, 2011). Emissions are then converted to global temperature change using an emission metric (Aamaas et al., 2013). This means that we allocate a future global temperature change due to current production and consumption emissions. The allocations from producers to consumers (in sectors and regions) require the global supply chain to be enumerated using economic production and trade data (Peters, 2008). Production often goes through several steps from extraction and refining to manufacturing and packaging, and finally to consuming markets. These linkages are represented in the global supply chain through monetary transactions. We normalize emissions by monetary output in each sector in each region, and allocate emissions according to purchases made by consumers. The result connects production and consumption, which are potentially geographically separated, and estimates the consumption that is driving current production emissions and hence future global temperature response.

All datasets and models introduce uncertainties in the analysis, thus we estimate uncertainties on the economic data, the emissions data and metric parameters in order to estimate uncertainties in the final results. We undertake the uncertainty analysis using Monte Carlo (MC) analysis, in which datasets and parameters are randomly perturbed according to predetermined distributions, and then sub-models are run sequentially to obtain distributions on the results (Granger Morgan et al., 1990). We isolate the

individual contributions to uncertainty on the final results by perturbing individual components independently, before running everything together to estimate total uncertainty. The analysis considers parametric uncertainties on the components, as opposed to structural uncertainties, which would include the comparisons of different models and datasets (Peters et al., 2012). The next section lists the background data, and shows how uncertainties are estimated, before running the models and discussing the results.

2.1 Datasets and models

We use multi-regional input-output (MRIO) analysis to link economic activities from production to consumption, capturing global supply chains at the sectoral level (Davis and Caldeira, 2010; Wiedmann, 2009). We source our economic input–output data from the Global Trade Analysis Project (GTAP) database version 8, which comprises domestic and trade data for the entire world economy in 2007 divided into 129 regions and 58 sectors (Narayanan et al., 2012). We use these data to construct an MRIO model, which connects all regions at the sector level (Andrew and Peters, 2013; Peters et al., 2011b). While GTAP does not provide uncertainty estimates on the economic datasets, it is possible to generate realistic uncertainty estimates for the GTAP database from proxy data. Since an MRIO database is an aggregation of multiple datasets, it inherits uncertainties from a number of sources, including: source data, base year extrapolations, balancing and harmonization procedures, allocations and aggregations (Wiedmann, 2009; Weber, 2008).

We use emissions data for the year 2007 from the Emissions Database for Global Atmospheric Research (EDGAR), for a number of pollutants (see Table 1), mapping these data to the regions and sectors of the GTAP database. Uncertainties in emission statistics for each pollutant derive from multiple sources, e.g. for CO_2: how much fuel is actually consumed, its carbon content, and how much of it is combusted. Additionally, to be consistent with top-down estimates, statistics are subject to adjustments and harmonization, and aggregated and grouped to economic sectors. Although national uncertainty may in some cases be large, global emissions are dominated by a small number of countries, thus the global uncertainty is mostly a reflection of these countries' data quality (Andres et al., 2012).

The estimated global temperature impact of emissions are calculated using the global temperature change potential (GTP) metric (Aamaas et al., 2013; Shine et al., 2005), which is essentially a parameterization of more complex climate models. The metric uses pollutant characteristics (atmospheric lifetime, radiative forcing) as input, and unlike the more commonly used Global Warming Potential (GWP) which only relates to radiative forcing, the GTP also includes estimates of climate temperature response (sensitivity) to changed radiative forcing in the atmosphere, which adds additional layers of uncertainties (Reisinger et al., 2010). We base our pollutant parameters on the ATTICA assessment (Fuglestvedt et al., 2010; IPCC, 2007, p. 212–213), and climate sensitivity and CO_2 uncertainties on the latest CMIP5 data (Olivié and Peters, 2013). The uncertainties on the other pollutants are drawn from several sources, but mostly following the IPCC Fifth Assessment Report (Myhre et al., 2013a).

2.2 General uncertainty relationships

It has previously been shown that economic and emissions data show a general pattern where relative uncertainty is inversely related to magnitude (Lenzen et al., 2010; Wiedmann, 2009; Lenzen, 2000; Wiedmann et al., 2008). The GTAP data used in our analysis follows the same trends, based on selected input-output (IO) data where uncertainty is derived from differences between the reported input data and the final data in the database after harmonization is done and balancing constraints are met (Table 19.6 in McDougall, 2001). These differences in data resulting from the harmonization process are available only for "*large sectors in large regions with large relative changes*", which implies that this relationship indicate the high-end of uncertainties estimates (McDougall, 2001). Figure 2 shows the relationship for this subset of economic data and uncertainties, with first-order power regression fits to the observations ($R^2 > 0.9$). The uncertainties are created from the difference between input and output values, relative to the input and output values, respectively. However, deriving uncertainties from

these differences is not straightforward, as there are many different methods based on different assumptions which will add additional uncertainties (e.g. comparisons of the difference of input and output values to the input, output or mean values gives different results). Because of this, we only use the general relationship between sector size and uncertainty, and not the parameters from Table 19.6 in McDougall (2001), when estimating sectoral uncertainties. Furthermore, we assume a similar relationship with the emissions data, based on a previous study of the UK Greenhouse Gas Inventory, where uncertainties were found using an error propagation model (Jackson et al., 2009).

The dataset allows the parameterization of a function mapping relative uncertainties to the magnitude of the data points. Following previous studies (Lenzen et al., 2010; Wiedmann et al., 2008), we assume the data follows a power function

$$r_x = ax^b \tag{1}$$

where a and b are coefficients. As there is very little data available to parameterize Eq. (1), we parameterize the relationship using two extreme data points (generally the uncertainty on the minimum and maximum values)

$$a = \frac{r_{\min}}{v_{\max}^b} \tag{2}$$

$$b = \frac{r_{\max} - r_{\min}}{v_{\min} - v_{\max}} \tag{3}$$

It is generally argued that developed countries have lower uncertainty than developing countries due to the strength of institutions (Narayanan et al., 2012; Andres et al., 2012). The terms $r_{\min}$ and $r_{\max}$ define the smallest and largest relative errors, respectively, and are functions of developed and developing regions where the latter is given twice the uncertainties of the first group (using the Kyoto Protocol groupings of Annex B and non-Annex B countries). This range is also sector- and region-dependent for the economic and emissions data, which we define below. The terms $v_{\min}$ and $v_{\max}$ refer to fixed minimum and maximum data values for sectors in a specific region, which is given the uncertainty of r_{max} and r_{min}, respectively. Figure 3 shows the functional relationship between sector sizes and uncertainties for economic and emissions data, respectively.

The lower threshold v_{min} is fixed for all regions in the economic and emissions datasets, giving sectors of the same size the same uncertainty, as the smallest sectors do not contribute much to the national totals. The upper threshold v_{max} can also be fixed to a certain sector size. However, uncertainties are likely to be regionally variable, as while a sector of e.g. 1 billion USD might be very large for some countries, it might not be large in other regions. To account for this, we argue that the sectors' importance should vary with their contribution to the nations' totals, e.g. gross domestic product (GDP) or total emissions. We therefore scale v_{max} according to the regions' GDP and total emissions, for the respective datasets, so that the sectors' importance in different regions is reflected by their uncertainties. Sectoral values larger than v_{max} are given the same uncertainty as values equal to v_{max}, to ensure that single large sectors do not affect the uncertainty on other large sectors (see details below).

The estimated uncertainties are used to create distributions of perturbations. We impose log-normal distributions so that distributions with small relative spreads closely resemble normal distributions, while distributions with large relative spreads are skew but avoid negative values (Fig. 4). The distributions are characterized using reported data as medians, and the spreads are (in order of decreasing preference) taken directly from the literature, derived from published analyses, or estimated. We define uncertainties as the 5–95 % confidence interval (90 % CI; equivalent to 1.64 standard deviations of a normal distribution). By randomly perturbing each data point, we assume no correlations in the uncertainties of economic and emissions data, which might not be accurate for some sector combinations (Peters et al., 2012). However, since little data exist, attempts to take this into account will further introduce other uncertain assumptions. Thus we do not adjust for correlations in these datasets. We do, however, undertake a simple sensitivity analysis on the parameter choices, by comparing

the final results on MRIO uncertainty with uncertainty from the GTAP table showing extreme observations.

Aggregations of the results (from sectors to regions and from regions to global) usually decrease the relative uncertainty, so that the national uncertainty is lower than individual sectors, and global uncertainty is in some cases lower than national uncertainty. This is a result of the summation effect, and the relationship between sector sizes and uncertainties. The largest sectors are given lowest uncertainties, so that the national uncertainty is largely a reflection of the uncertainty of the largest sectors. As an example of the summation effect, the relative uncertainty r of adding $M \pm S$, n times, is

$$r = \frac{S/M}{\sqrt{n}} \tag{4}$$

assuming no correlations. To illustrate this effect, we show the uncertainty results at multiple levels.

2.3 Economic data (multi-regional input–output model)

The total sectoral output $\boldsymbol{x}$ of a region's economy (a vector) is the sum of intermediate consumption $\mathbf{A}\boldsymbol{x}$ and final consumption, $\boldsymbol{y}$ (Miller and Blair, 1985):

$$\boldsymbol{x} = \mathbf{A}\boldsymbol{x} + \boldsymbol{y} \tag{5}$$

where $\mathbf{A}$ is the inter-industry requirements matrix, which is equivalent to the technology used in each sector's production. We solve for the total output

$$\boldsymbol{x} = (\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{y} \tag{6}$$

where $(\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse $\mathbf{L}$. Emissions are estimated for a given y by first estimating the output, and then linking to sectoral emission intensities, $\boldsymbol{F}$. This gives the direct and indirect emissions (supply chain) emissions

$$\boldsymbol{f} = \boldsymbol{F}\mathbf{L}\boldsymbol{y} \tag{7}$$

The economic data from GTAP is represented in a multi-regional input–output (MRIO) model, which is constructed from a number of smaller datasets. The GTAP dataset itself is based on a large number of smaller datasets (such as national IO tables and trade data from UN's COMTRADE database), which are harmonized to remove inconsistencies (Andrew and Peters, 2013; Peters et al., 2011b; Narayanan et al., 2012). The construction of an MRIO table from the GTAP data is explained in detail elsewhere (Peters et al., 2011b). In the MC analysis, we perturb the components of the GTAP database (e.g., domestic IO data and international trade data) and not the resulting MRIO. In other words, we estimate the uncertainty of the MRIO data based on the uncertainty in the data used to construct it. This ensures that the uncertainties of the final model reflect the underlying uncertainties of the various input data. We construct the perturbed $\boldsymbol{L}$ and $\boldsymbol{y}$, before allocating the direct emissions $\boldsymbol{F}$ (which are also perturbed) to consuming regions and sectors.

We calibrate the uncertainty relationship (Eq. 1) for the GTAP data using several datasets. From the trend lines created from the GTAP table (Fig. 2), we find the smallest uncertainty on the largest sectors to be at approximately 5 %. We therefore let 90 % of perturbed values fall within 5 % of the median, and set $r_{\text{min}} = 5\,\%$ for the largest sectors (where v_{max} apply).

The upper threshold v_{max} is defined by the regions' GDP so that a sector of a specific size will have a larger importance (and hence a lower uncertainty) in a small region than in a large region. We use the UK data provided by Lenzen et al. (2010) to explain the range of uncertainties in a single economy. In this dataset the largest sectors have the smallest error, and following the trend line we find that the largest value is about 4 % of UK GDP. We use this to define the upper threshold $v_{\text{max}} = 4\,\% \times \text{GDP}_r$, which means that sectors at or above this value will be given the lowest national uncertainty (r_{min}). Figure 3 shows the result of the implementations, where the lines indicate the range of developing and developed regions' sector sizes and uncertainties.

For the smallest sectors we set v_{min} equal to 1 USD and assume $r_{\text{max}} = 100\,\%$, due to the lack of more precise regional uncertainty data. The 1 USD relates to a small

value often used in the GTAP database (Peters, 2006). These parameters may seem somewhat arbitrary, but these choices are not overly important. A value of 1 USD in an IOT is exceedingly small (it represents the economic relationship between two sectors over one year). Indeed, analysis shows that removing small values has negligible effect on the estimates consumption based emissions (Peters and Andrew, 2012). Thus, 1 USD is effectively zero in our dataset. It could also be argued that the value of 1 USD is highly uncertain and should have large uncertainty. Giving values smaller than this higher relative uncertainty causes highly skewed log-normal distributions for the perturbations (see Fig. 4). The GTAP dataset has values as low as 7×10^{-35} causing r to be $6 \times 10^{6}\,\%$. Such highly skewed distributions for data points with small medians ($\ll 1$ USD) can lead to large imbalances in the table.

An IO model is balanced so that gross input equals gross output, a fundamental characteristic of input–output models (Leontief, 1970). The same applies for a multiregional model (MRIO). When perturbing the coefficients in an IO table, it ultimately upsets the balance. In principal, the IO table can be rebalanced, but given the size of the systems (about 7500 × 7500 matrices), rebalancing is prohibitively computationally expensive, and may reduce uncertainties as the perturbed values are changed. To retain balance, we therefore choose not to rebalance, which effectively causes the "unbalanced" component to be shifted to the value added. A concern is that the value added may become unrealistic (e.g., negative) as a consequence. The MC algorithm specifically outputs value added components to allow cross check imbalances with the raw data, and we find the distributions of the value added at the sector level to be within expected uncertainty bounds given the size of the value added. This is partially because of the parameterization of uncertainty we have used, and partially because the perturbations tend to cancel (the sum of random numbers). Thus, we can justify not rebalancing our perturbed IOTs and assume the imbalances are allocated to the value added (without having a large effect on the value added). This approach is followed by others (Lenzen et al., 2010).

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For a simple sensitivity analysis of the input uncertainties, we also run the MC model with uncertainties according to the fit of the GTAP table uncertainties (trend line relative to final values, due to better fit; Fig. 2). This vastly increases the uncertainties of all sectors, and we do not constrain the upper or lower uncertainties, meaning that very small sectors will be given unrealistically large uncertainties (1 USD gives $r = 1 \times 10^9$ %). This exercise is only valid for the data it represents; large sectors in large countries, but is useful to facilitate the discussion about uncertainties in economic data. We discuss these results when exploring MRIO uncertainties, but do not include this when combining uncertainties.

2.4 Emission statistics

The pollutants considered are listed in Table 1, which cover anthropogenic emissions for the year 2007 which have an effect on climate. We do not include emissions from short cycle biomass burning, as this is considered to have a short lifetime in the atmosphere due to regrowth. The dataset originally includes CO_2 emissions from forest fires and decay, which is a mix of natural and anthropogenic emission. Extracting the anthropogenic emissions and mapping them to agricultural sectors would require crude assumptions. We therefore do not include emissions related to forest loss, but acknowledge that it would increase global CO_2 emissions with roughly 12 % (van der Werf et al., 2009). The EDGAR dataset only provides crude information on uncertainty at the global level for some species (European Commission, 2011). Therefore, global and regional uncertainties in emissions are taken from a variety of sources (Table 1). Global fossil-fuel CO_2 emissions statistics are independently produced by several organizations, but they generally agree with each other within about 5 % for developed countries and 10 % for developing countries (Andres et al., 2012). The CO_2 emission estimates are all based on energy data, and globally the emissions are thought to have an uncertainty of ±10 % using a 95 % CI (UNEP, 2012). Global SO_2 emissions have an estimated uncertainty of between ±8 % and ±14 %, while regional uncertainties may be as large as ±30 % (Smith et al., 2010). For CH_4, N_2O and F-gases, the uncertainty

of global emissions have been estimated as ±21, ±25 and ±17 %, respectively (UNEP, 2012).

Table 1 shows parameters and uncertainties for each pollutant used as median values in the perturbations. Very little data exist on uncertainty of emissions by sector, especially on a pollutant and regional level. Lenzen et al. (2010) used a table of selected sectors of UK CO_2 emissions to find uncertainties, originating from Jackson et al. (2009). According to the regression of the data points, within the limits of the data points, there is a spread of uncertainties of roughly 10 times (Fig. 2 in Lenzen et al., 2010). We therefore estimate sectoral uncertainty using the same general relationship as with the economic data (Eq. 1), where the uncertainty of global emissions is used as a proxy for the lowest uncertainty estimate of the largest sectors ($r_{\min}$) and the smallest sectors' uncertainty is scaled by 10 times ($r_{\max} = 10 r_{\min}$).

We assign developing countries an $r_{\min}$ and $r_{\max}$ which are double those of developed countries. We define $v_{\min} = 1$ kt and $v_{\max} = 5$ % of regional emissions. This dependence on total regional emissions shifts the function so that a sector of a specific size will have a larger importance (and hence a lower uncertainty) in a smaller region than in a larger region (Fig. 3). We do not distinguish between different sources of the same pollutant, due to lack of information at the sector level. This is, in some cases, a crude simplification (e.g. when comparing uncertainties in emissions of certain pollutants from agricultural sectors and power generation). Similarly, for the emissions data, we set $v_{\min}$ equal to 1 kt emission. Values below this (as with economic data) have little impact on the footprint of regions and sectors, and are therefore given zero uncertainty. Estimates of uncertainty for some pollutants for some of the nations do exist, which is included in the calculations. Where regional information is available (e.g. for CO_2 emissions from China), we use that to set the minimum uncertainty, which will also define the steepness of the uncertainty sector size relationship.

With every sector data point having an uncertainty, we create perturbations which we can sum to get a bottom-up estimate of the national uncertainty. Table 2 shows several perturbations of sectors (x_{in}) for region r. Each perturbation i leads to a new national total (X_i). However, independent uncertainty estimates of national totals (e.g. national emissions) that may be available for some regions may conflict with our bottom-up distributions on the national totals ($\boldsymbol{X}_\mathrm{N}$). When summing the perturbed sectors x_{in} for a region, it is unlikely that the distribution of $\boldsymbol{X}_\mathrm{N}$ will be the same as the known uncertainty in X.

Additionally, the uncertainty in $\boldsymbol{X}_\mathrm{N}$ will depend on the number of elements contributing to the sum, according to standard propagation of uncertainty rules (RSS, root sum square; see earlier discussion on the summation effect). In practice, the uncertainty of X may be based on several lines of evidence, which may even exclude sector-based data. To ensure that we can reproduce the top-down uncertainty estimates of X, we use constrained optimization (using a quadratic programming (QP) methodology) to minimally adjust the perturbations of x_{in} to a given distribution of the $\boldsymbol{X}_\mathrm{N}$ (Table 2).

Given that we can adjust one iteration so that it sums to a fixed X, we then give X a distribution based on known national uncertainties, and thus, each iteration of X is used to balance the same iteration of the disaggregated sector data (x_{in}). This ensures that the sum of sectors (X_i) always gives a $\boldsymbol{X}_\mathrm{N}$ with a known uncertainty. The cost of this adjustment is that the spread of the large values in each region (e.g. a large sector) are adjusted to fit the constraints. To meet the criteria of e.g. a narrower distribution on the aggregated values, the large values have to be given a narrower distribution as well. This methodology allows us to give realistic uncertainties on each x_{in} leading to an $\boldsymbol{X}_\mathrm{N}$ with a known uncertainty. We do not perform such balancing on the MRIO input data (previous section) as it is too computationally expensive, and there is little top-down data on uncertainties in economic data.

2.5 Emission metrics

To link emissions to temperature change, we use the global temperature change potential (GTP) as a metric to compare and aggregate pollutants (Shine et al., 2007). This gives an estimate of the global mean surface temperature change due to a pulse

of emissions from a specific pollutant, and is a simple way of modeling the much more complex climate system, and its response. Uncertainties in metric values can arise from a range of factors: pollutant parameters (radiative forcing and lifetime) and the response of the climate system. Although it has been shown that the GTP may have larger relative uncertainties than the alternative metric global warming potential (GWP) (Aamaas et al., 2013; Reisinger et al., 2010), the GTP directly links to global temperature change and is thus arguably more policy relevant (Shine et al., 2005). In addition, the physical interpretation of the GWP is less clear and the metric has been criticized by many authors (Peters et al., 2011a; Shine, 2009). The GTP metric is calculated using impulse response functions, which explain the interaction of pollutant i in the atmosphere (IRF_i) and the climate system (temperature) response to a pulse emission (IRF_T) with specific radiative forcing (RF) and atmospheric lifetime.

We briefly describe the metric equations here, and refer to existing literature for more details (Aamaas et al., 2013; Fuglestvedt et al., 2010; Olivié and Peters, 2013; Myhre et al., 2013b). The absolute GTP (AGTP) for each pollutant i is defined as

$$\mathrm{AGTP}_i(H) = \int_0^H \mathrm{RF}_i(t)\mathrm{IRF}_\mathrm{T}(H-t)\mathrm{d}t \tag{8}$$

where the Radiative Forcing (RF) for a pulse emission is

$$\mathrm{RF}_i(t) = \mathrm{RE} \times \mathrm{IRF}_i = A_i \exp\left(-\frac{t}{\tau_i}\right) \tag{9}$$

where t is time [years], H is the time horizon [years], A_i is the radiative efficiency for pollutant i [W (m^2 kg)$^{-1}$], and τ_i is the decay time for pollutant i [years]. The AGTP metric is dependent on the IRF of temperature, which incorporates the climate system response in global mean surface temperature to a given radiative forcing. The climate response is modelled using two decaying exponential functions representing: (1) the relative fast response of the atmosphere, the land surface and the ocean mixed layer, and (2) the relative slow response of the deep ocean (Peters et al., 2011a),

$$\mathrm{IRF_T} = \sum_{j=1}^{J} \frac{c_j}{d_j} \exp\left(-\frac{t}{d_j}\right) \tag{10}$$

where J is the number of decay terms (usually two), c_j is a component of the climate sensitivity [K (W m^2)$^{-1}$], where the total climate sensitivity $\lambda = \sum c_j$, and d_j is the decay time [years] of component c_j. These two functions are explained by lifetimes and climate sensitivity for the individual components (Table 3). The λ explains the change in equilibrium global-mean temperature due to forcing by a pollutant in the atmosphere. We parameterize the IRF according to the results from CMIP5 covering 15 different climate models (Olivié and Peters, 2013). This dataset is parameterized by relatively short climate runs (140–150 years), and thus it is more representative of the short-term climate response (less than 100 years) compared to the equilibrium response (see Olivié and Peters (2013) for details). Nevertheless, the dataset leads to a median $\lambda = 0.75$ K (W m^2)$^{-1}$ (equivalent to 2.8 °C global-mean temperature increase), which is consistent with the climate response (sensitivity) of a doubling of CO_2 concentration in the atmosphere within the range of 1.5 to 4.5 °C (IPCC, 2013).

As CO_2 has a more complex interaction in the atmosphere and can not be sufficiently modelled with a single exponential decay, we define the RF for CO_2 as a sum of exponentials (Aamaas et al., 2013):

$$\mathrm{RF}_{CO_2}(t) = A_{CO_2}\left\{a_0 + \sum_{i=1}^{I} a_i \left(1 - \exp\left(-\frac{t}{\tau_i}\right)\right)\right\} \tag{11}$$

where a_i is the weight of each exponential, which by definition have to sum to one ($\sum a_i = 1$), and I is the number of exponentials. We follow Joos et al. (2013) and use four exponentials and weights, and randomize the multiple lifetimes and coefficients

so that the coefficients always sum to 1, following Olivié and Peters (2013). The use of four different time scales was found to be sufficient to model CO_2's behavior in the atmosphere compared to advanced climate models (Olivié and Peters, 2013). Correlations between the parameters were implemented for CO_2 and $\mathrm{IRF_T}$, also based on Olivié and Peters (2013), but the effect of the correlations on temperature results was found to be small (less than 1 % of AGTP50 value for CO_2).

Estimates from the literature are used as the median (Fuglestvedt et al., 2010) and estimates of uncertainty as spread of the distributions (Tables 4 and 5). For the non-reactive pollutants, we randomized the single RF and lifetime values, as these are represented by only a single decay function. The RF used in the calculations includes the indirect effects of chemical reactions from the ozone precursors (CO, NO_x and NMVOC), which were perturbed similarly as the other pollutants. This accounts for three indirect forcing effects: formation of O_3 (causing positive RF by CO, NO_x and NMVOC), changing CH_4 levels (causing positive RF by CO and NMVOC, and negative RF by NO_x), and CH_4 induced O_3-effect (causing positive RF by CO and NMVOC, and negative RF by NO_x) (Aamaas et al., 2013). The indirect effect of SO_2 is included by scaling the metric value, where the indirect effect of SO_2 is estimated to be about 175 % of the direct effect (Aamaas et al., 2013). This is a crude estimate, and while the indirect effect may be more uncertain than the direct effect, we use the same uncertainty for the direct and indirect effects due to lack of pollutant specific data (Boucher et al., 2013).

Our analysis of uncertainty contributions from emissions and metric parameters uses Absolute GTP (AGTP) values with units of temperature change (in Kelvin or °C). When later allocating temperature data in the economic model, we also use GTP values in units of CO_2-equivalent emissions for comparison. The GTP values are calculated by normalizing the AGTP values with reference to the AGTP values for CO_2. When we connect the components for a full MC analysis, we choose a single time horizon for computational reasons. As discussed elsewhere (Fuglestvedt et al., 2010), choosing a time horizon includes value judgment, and is not based solely on a scientific judgment. We choose to focus on the impact at 50 years (AGTP50 and GTP50), as this is both consistent with current literature (Myhre et al., 2013b), and within reasonable time for when to expect global warming to exceed 2° (Joshi et al., 2011; Peters et al., 2013).

3 Results

Estimated uncertainties are used to create distributions on all data points. To analyze how various stages of the cause-effect chain contribute to overall uncertainty, we introduce uncertainty separately in each part of the chain before combining them all together (Fig. 1). We first show uncertainties resulting from (1) the economic data only, (2) the emissions data only, and (3) the metric calculations only. The final section (4) connects these three parts together to follow uncertainty through the entire cause-effect chain. The results show uncertainty propagation from consumption to global temperature change. The analysis is based on 10 000 MC runs.

3.1 MRIO uncertainty

In this section, we assume there are no uncertainties on the territorial emissions data or emission metrics, thus the MRIO model uses unperturbed median estimates of GTP50 values for all pollutants when allocating emissions to consumers, and uncertainties are purely dependent on parametric uncertainty in the input data into the MRIO. In our analysis each of the 129 countries has 57 producing sectors (not including households as they are considered final demand in the model, and therefore not included in the processing), and thus the MRIO table has 7353 rows and columns. We emphasize here, but discuss later, that we consider parametric uncertainties and not structural uncertainties.

Table 6 shows uncertainties in emissions embodied in imports and exports, as well as consumption, due to perturbations only on the economic dataset. The exports indicate goods that are produced domestically but consumed abroad, while the imports indicate goods produced abroad but consumed domestically. The uncertainties

in exported emissions are solely due to uncertainties in domestic economic data, thus reflecting the pattern of developed countries having higher uncertainties. Uncertainties in imported emission are generally higher than exported emissions, as the imports come from a number of different regions of which many may have high uncertainties (e.g. emerging and developing economies).

For the largest consumption paths, the consumption perspective is not substantially more uncertain than the corresponding territorial view due to economic uncertainties. Following the largest international fluxes embodied in trade from Davis and Caldeira (2010) aggregated over all sectors, we find 2 % uncertainty in emissions embodied in products exported from China to USA, 2 % uncertainty from China to Western Europe, 3 % from China to Japan and 1 % from USA to Western Europe from economic uncertainties only. For smaller paths, there are much higher economic uncertainties. More than 20 % of the international trade routes have a higher uncertainty than 10 % (total number of trade routes is 128 regions × 128 regions), while the median of all is 6 % uncertainty. The uncertainties in consumption emissions for the top emitters are very low for two reasons: (1) the effect of summations and aggregations reduce the uncertainties on the national level (Eq. 4); much higher values are seen on a sectoral level), and (2) the distributions we give the perturbed data in the larger sectors are relatively small.

Since we start from the raw GTAP data to construct the MRIO table, and normalize and invert the MRIO table, a vast number of summations and multiplications are done with the initial perturbed data. Following RSS uncertainty propagation, the relative uncertainty will decrease when adding equally sized numbers with equally sized uncertainty (not an unrealistic assumption for IOA). Thus, the relative uncertainty on the sum of a row in the MRIO (the output) will depend on the number, n, of large data points (Eq. 4). This problem can be avoided by using a quadratic programming approach to rebalance the sum to a given uncertainty (as we do for the emissions data), but we do not do this as (a) it is too computationally expensive, and (b) it would require balancing the entire MRIO table to get consistent sums. This problem is difficult to negotiate given the size of the database we are using, and consequently this exerts a downward pressure on MRIO uncertainties. Because of this, and because uncertainty ranges of input values are small for the largest and most important sectors, the final results have small uncertainties. A valid question is then how reliable the uncertainties are.

The raw uncertainties from Table 19.6 in the GTAP documentation (Fig. 2), however, act as a simple sensitivity analysis to our applied uncertainties. When we use these we find that the uncertainties are much larger for the largest emitters (between 160 % and 400 % uncertainty for consumption-based emissions), and for small and medium sized countries the uncertainties becomes unrealistically large. This is expected as the input uncertainties are outliers in the GTAP database, thus the uncertainties are known to be large. As a consequence the vastly perturbed values lead to ill-defined MRIO tables (outside of machine precision), which will compromise accuracy in the final results (see Sect. 2 on skew distributions and small data points). However, as discussed earlier, using the difference between input and output values as a proxy of uncertainty is not straightforward. E.g. the first data point in Table 19.6 indicate an input values of 2 billion USD and an output value of 132 billion USD, where the difference (relative to the initial value) can be interpreted as a change of 6500 %. This *uncertainty* is vast, and many data points have much larger differences. Because of these difficulties, and since the results are only valid for specific sectors, we don't show regional results from this analysis, but only use it for illustrative purposes.

Overall, we find small uncertainties on the MRIO results, however, the uncertainties on the end results are a function of the uncertainties on the input values, as shown by the sensitivity analysis. Furthermore, the input uncertainties are estimated from small amounts of data and many assumptions, making the uncertainty estimates on the end results less robust. Although our results are supported by other studies that have performed parametric uncertainty analysis (Lenzen et al., 2010; Bullard and Sebald, 1988; Peters, 2007), structural uncertainties in MRIO analysis is found to be larger (Peters et al., 2012). Thus we suggest that MRIO uncertainty may be best evaluated

using a combination of structural uncertainties (model comparisons) and parametric Monte-Carlo uncertainties.

3.2 Emissions

At the global level, uncertainties in emissions are known from previous studies (Table 1), which are used to estimate uncertainties of emissions occurring from production at the sectoral and regional level. Figure 5 shows the uncertainty of all data points (7482 sectors, 129 regions and global aggregations) for all pollutants. Each data point's uncertainty is dependent on the sector size, the region's GDP and whether the region is a developed or developing country. Different activities are associated with different emissions, thus not all sectors in all regions include emissions from all pollutants. Additionally, the PFCs and HFCs groups are aggregates of several pollutants, thus the spreads are based on different amounts of data.

The red boxplots in Fig. 5 shows the sectoral distributions of the relative uncertainties, not including data points with zero uncertainties. Aggregations of sectors to individual countries (blue boxplots) lower the uncertainty ranges, depending on the sectors' impact on national totals (NF_3 is a special case, where only one sector in each region has emissions, thus sectoral and regional uncertainties are the same). The median values for the boxplots indicate the skewness of the distributions. The distributions often have two distinct peaks (not visible in the boxplots), which are developed and developing countries, where the latter group has higher uncertainty. For CO_2, NH_3, NO_x and SO_2, regional information has been used instead of global uncertainty as a proxy for the lowest uncertainty in the largest sectors in some countries. The global aggregations are results of national totals, which are dominated by large regions (e.g. China and USA). The bottom-up global uncertainties are not constrained by top-down estimates, as we are not using aggregated global emissions in the end results. They are, however, all (except NF_3 due to few data points) lower than the input estimates from Table 1 due to the aggregation effect. Small regions with low emission and high uncertainties thus have little effect on the global uncertainties.

The well-mixed GHGs (WMGHG; CO_2, CH_4, N_2O, HFCs, PFCs, SF_6, NF_3, CH_4) generally have lower emissions uncertainties (5 % uncertainty for the aggregated sum) than the short lived pollutants (BC, OC, SO_2, NH_3; 12 % uncertainty) and precursors (CO, NMVOC, NO_x; 20 % uncertainty). The WMGHGs accounted for 39.4 ± 0.9 Gt CO_2-eq. emissions (using GTP50), while the short-lived pollutants accounted for -4.6 ± 0.5 Gt CO_2-eq. and the precursors accounted for 0.4 ± 0.1 Gt CO_2-eq. (where the two last groups have a mix of warming and cooling effects). Uncertainties in pollutant aggregates for emissions (tonnes) and GTP50 (CO_2-eq.) values only include emission uncertainties, but are different due to different weighting of pollutants and due to mixing of cooling and warming effects. Uncertainties of territorial emissions from developing countries (54 % of global emissions using GTP50) have a median value of 32 %, while developed regions have a median uncertainty of 16 %. These numbers are dominated by the uncertainty of CO_2, and usually only small variations are seen due to other pollutants.

Globally, most emissions occur in the electricity generation sector (28 % of global emissions using GTP50) and manufacturing sectors (25 %) (see Supplement for sector aggregations). Uncertainties in emissions (tonnes) from electricity range from 10 % for CO_2, 18 % for SO_2 and 58 % for NO_x, which are the most important pollutants (which has the largest contributions to the sectoral GTP50 value). For energy-intensive manufacturing, CO_2 (3 % uncertainty), SO_2 (5 %), and CH_4 (53 %) are the most important pollutants. In the non energy-intensive manufacturing sectors, CO_2 (3 % uncertainty), SO_2 (10 %), and HFCs (12 %) dominate.

For agriculture, CH_4 (21 % uncertainty) and N_2O (26 %) are equally important to the GTP50 value, while CO (37 %) comes third. CH_4 has less uncertainty coming from agriculture than energy-intensive manufacturing, since for CH_4 the agriculture sector is much larger, which is consistent with top-down estimates (Kirschke et al., 2013). The household sector emits mainly CO_2 (7 % uncertainty), BC (151 %) and OC (139 %), due to household fuels and private transportation. The transport sectors consists mainly of CO_2 (5 %), SO_2 (6 %) and NO_x (16 %). Mining, services, and food sectors are small in

a production view, and consist mainly of CO_2 (2 %), CH_4 (16 %) and SO_2 (6 %). These estimates are aggregates of sectors and regions (and gases for HFCs and PFCs), thus disaggregated data have larger uncertainties.

3.3 Emission metrics

Metric (temperature) values have an uncertainty range for the different pollutants and different time horizons, due to the perturbed metric parameters (RF, lifetime, and climate sensitivity). Figure 6 shows all pollutants on the same scale using AGTP for 2007 global emissions, with both relative and absolute uncertainties. The net temperature response (black dotted line) goes from negative to positive over the first few years, before the short-lived species decay and the net effect becomes dominated by CO_2 in the long run. The relative and absolute uncertainty of the net effect is largest in the first few years, and becomes roughly stable from 50 to 100 years. The strong temperature effects of SLCFs and thus the high absolute uncertainties of the mix of pollutants increase the net uncertainty in the first few years, but CO_2 dominates the uncertainty after 20 years.

The top contributors to absolute uncertainties in the first year are SO_2, BC and NH_3. BC and SO_2 have similar relative uncertainties, but since the emissions of SO_2 are much larger, it has five times the absolute uncertainty. OC, BC and SO_2 have the largest uncertainties after approximately 10 years (except for NH_3 due to its significantly larger RF uncertainty), as the uncertainties are dominated by RF and climate sensitivity uncertainties. NO_x has a very high relative uncertainty after 7 years because its temperature effect goes from positive to negative around this time.

Figure 7 shows a breakdown of the parameters contributing to relative uncertainty of the AGTP values by pollutant (see Supplement Figure for absolute uncertainties). MC runs with separate metric components individually perturbed were done to isolate the individual contributions to uncertainties. For comparison, uncertainties on global emissions are also included in the graph, although not included when perturbing all components. Uncertainties on emissions and RF do not depend on time horizon, thus

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they are straight lines. However, as the precursors have combined effects (see methods) the uncertainty on RF on CO, NMVOC and NO_x actually change with time due to the different effects having different lifetimes.

For the first three years the total uncertainty for most pollutants (except the SLCFs: BC, OC, SO_2 and NH_3) is completely dominated by the first decay parameter of the climate sensitivity, which has a median value of 2.6 ± 1.2 years (Olivié and Peters, 2013). For the WMGHGs, the parameter continues to dominate to approximately 6–8 years where the uncertainty of the climate sensitivity component takes over and continues to dominate to at least 100 years. Between them they explain the largest contributions of uncertainties to the metric values for all time horizons. While the decay parameter explains the large uncertainties in the first years, the climate sensitivity parameter explains the increasing relative uncertainties towards 50 and 100 years. The climate sensitivity parameters are highly sensitive to time horizon since they have different effects at different times. For SO_2 and NH_3, the first years are also effected by high uncertainties from RF. Other short lived pollutants (BC and OC) have large contributions from both emissions and RF values.

At 50 years, CO_2 and CH_4 have additional significant contributions to uncertainties from lifetimes. Since they both have lifetimes within the ranges of the graph, they show variability with time horizon. The shorter and longer lived pollutants show little variations in lifetime uncertainties over time horizons, as lifetimes are either too short or too long to have any effect within 100 years at this scale. The uncertainty on lifetime for several gases are assumed (Table 5), however, the small impact from lifetime uncertainties on the metric values indicate that small changes of the median lifetimes will for most pollutants have very little effect. At 50 years the short-lived pollutants have uncertainties in the range between ±95 and ±165 %, while the WMGHGs have uncertainties in the range between ±35 and ±70 %. The precursors have uncertainties around ±65 %.

After 100 years, only the WMGHGs still have a significant temperature effect, which means that the SLCFs do not contribute with absolute uncertainties. In relative terms, shorter lived pollutants have a rise in uncertainties from 50 to 100 years, while the

opposite is true for the longer lived pollutants. The last group is then completely dominated by climate sensitivity uncertainties. Most pollutants have relatively low uncertainty contributions from emissions as the global estimates are low, except for BC and OC. On a regional and sectoral level, the uncertainties from emissions are usually much more dominant, which shifts the total uncertainties at all time horizons.

The literature consists of both studies which allocate emissions using the absolute metric (AGTP) and the normalized metric (GTP). The GTP metric values are scaled with the AGTP values for CO_2. When running the MC analysis we create AGTP values for every iteration, which implies that CO_2 always will be normalized by itself (by definition, $GTP_{CO_2} = 1$). Therefore, the uncertainties of total emissions using GTP values are quite different to AGTP uncertainties since the dominant species (CO_2) has no metric uncertainty, and the uncertainties on other species are potentially amplified due to the uncertainty of $AGTP_{CO_2}$ values.

A second effect of using the GTP values is that the normalization of AGTP values include the climate sensitivity in both the numerator and denominator, which means that GTP values are less sensitive to climate sensitivity uncertainties than AGTP values (i.e. uncertainties are correlated). Table 7 illustrates the difference between uncertainties in AGTP and GTP values. GTP uncertainties are typically ±10–15 percentage points below those of AGTP, and since the $AGTP_{CO_2}$ uncertainties are not strongly dependent on time horizons, they do not affect the uncertainties over different time horizons for other pollutants' GTP values much.

A few other studies have investigated the uncertainties of AGTP and GTP values, but it is difficult to compare those which have as there are many different sources of uncertainties from many different models and datasets. Our GTP uncertainty results are generally higher than Olivié and Peters (2013) estimates, since we also include uncertainties on lifetimes and RF values of non-CO_2 species. Their GTP50 uncertainties for BC (-62 ± 67 %), CH_4 (-38 ± 48 %), N_2O (-16 ± 25 %) and SF_6 (-17 ± 25 %) are higher than their GWP uncertainties, mainly due to the dependence on the uncertain climate response (Olivié and Peters, 2013). An other study (Fuglestvedt et al., 2010) found similar uncertainties for GTP50 values for BC (around 200 %) and smaller values for CH_4 (50 %) compared to our results, and essentially zero for N_2O, when only looking at sensitivity to the climate response. N_2O is a special case as it has a similar average lifetime to CO_2, thus it has similar climate sensitivity uncertainty as CO_2, which can be seen in Fig. 7 for AGTP values. The normalization of GTP therefore cancels the climate sensitivity effect. Based on an evaluation of several studies, Myhre et al. (2013b) assessed the uncertainty of CH_4 for GTP100 to be ±75 %, which is close to our estimate. Furthermore, Joos et al. (2013) found uncertainties for CO_2 AGTP values at 50 (±45 %) and 100 years (±90 %), based on the spread of multiple climate models. Overall, we find the uncertainties to be consistent with other studies, but highly variable depending on datasets and choices.

3.4 Uncertainty on all components

Total uncertainties in production- and consumption-based emission estimates reflect a combination of uncertainties from the economic data (IO data for regions and sectors), emissions data (tonnes of the pollutants occurring in regions and sectors), and metric parameters (RF and lifetime for the pollutants, and the resulting climate response). Additionally, the emissions of a region in a consumption perspective is a combination of domestic emissions as well as emissions occurring in other regions (due to emissions embodied in trade), which changes the mix of pollutants and inherits uncertainties from the regions and sectors they occur in. To facilitate our discussion we aggregate the 58 economic sectors (post analysis) to 9 sectors. The results are strongly dependent on different perspectives: (1) production and consumption, (2) relative or absolute metric values, (3) time horizon of metric, (4) global, regional or sectoral level, and (5) mix of pollutants included. To illustrate the largest differences, we focus on comparing points 1, 2 and 4, as 3 has been discussed extensively elsewhere (Myhre et al., 2013b).

In the allocations of metric values in the MRIO model, we choose to use 50 year time horizon, as discussed earlier: it is consistent with other recent studies, and consistent

with the 2° policy target. Because of the differences between absolute and relative metric uncertainties, we compare both when including perturbations on all components in the last section.

Figure 8 shows uncertainties from the components with aggregated sectors and the top emitting regions, using GTP50 production emissions. The three different bars represent individual MC runs with only the respective components perturbed. At the sector level, the uncertainties in emissions data is generally the smallest (from 4 % to 20 % for sectors), except for households where large and highly uncertain emissions of BC and OC occur. Uncertainty in metrics has a range from 14 to 64 %, being especially large in sectors with non-CO_2 emissions (e.g. agriculture and mining). Pollutants with higher relative uncertainty on emissions compared to uncertainty on metric values at GTP50 (including BC, OC, and NF_3 at disaggregated levels), will tend to give higher uncertainty on emissions, while the other pollutants will give higher uncertainty on metrics.

The sector aggregation means that high and low uncertainties from different sector sizes are mixed, and thus single sectors like construction have a higher uncertainty than the aggregated sector Services. Disaggregation from the global sector perspective to national level and further to sector level reveals that emissions uncertainties are a function of aggregations (sectoral uncertainties are adjusted to specific national uncertainties), while the metric uncertainties are not directly dependent on sector aggregation and will therefore not scale the same way. Consequently, disaggregated levels generally find much higher emission uncertainties than metric uncertainties. For the top 10 emitters, disaggregated sectoral emission uncertainties have a median value between 13 and 67 percentage points above the national aggregate, while the metric uncertainties have a median value between 4 and 16 percentage points above the national aggregated level.

Furthermore, emission uncertainties are scaled according to sector sizes, whereas metric uncertainties are not. This means that emission uncertainties are a combination of mix of pollutants and mix of sector sizes, while metric uncertainties only reflect the mix of pollutants (where uncertainty is dominated by temperature response). This makes the global sectoral and national level quite different, since the national level represent various sector sizes with uncertainties according to the functional relationship, while the global sectors might only represent large or small sectors. Because of this, emission uncertainties usually dominate at the national level as the regions are less aggregated (each region consists of 58 sectors) than the global sectors (each consisting of 129 regions). The difference in regional uncertainties is attributed to different mix of territorial pollutants being emitted, the sector sizes, size of economy and if the regions are developed or developing nations.

Uncertainties from the different components do not linearly contribute to total uncertainty in the end results, thus we calculate the total uncertainty in two different ways: an MC run with everything perturbed, and a RSS approach combining the individual components. While the MC run is considered the more robust method since it takes into account all data points, including the effect of error cancelling, the RSS method is an approximation of error propagation which assumes no correlation and normal distributions. The two methods agree in most cases, which imply that there are only small correlations between the components and that the global-level data is close to normally distributed. This further implies that a full computationally intensive MC run with all components perturbed might not be necessary in ideal cases, as the RSS method can approximately derive the results.

Figure 9 shows uncertainties from the consumption perspective, thus including MRIO uncertainties. In general, the emissions embodied in imports and exports inherit uncertainties from the economic data of the region where the emissions occur. Consumption emissions include territorial emissions and emissions from imports, while they exclude emissions from exports. Since our MRIO uncertainties only include parametric uncertainties they tend to be small due to the cancellation effect discussed earlier, which is consistent with other similar studies (Lenzen et al., 2010; Wilting, 2012; Bullard and Sebald, 1988; Peters, 2007). Structural uncertainties, including differences in data sources, MRIO models and definitions of consumption-based emissions, may be a larger source of uncertainty (Andrew and Peters, 2013). The differences in

the datasets and methods used to calculate consumption-based CO_2 emissions have shown to be relatively small, with roughly 10 % for USA for 2007 (Peters et al., 2012). Although various studies use different input data and models, Peters et al. (2012) found the results of major emitters to be robust across studies, even though 10 % differences are not uncommon.

The top emitting regions are large economies, and therefore have mostly large economic sectors and therefore low aggregated uncertainties. The consumption perspective also mix pollutants in regions and sectors since the supply-chain is taken into account, leading to dilution of the sectoral and regional variability since multi-sectoral dependence for a single consuming sector is common (e.g. the production of a car needs input from other sectors, especially electricity). Households are considered final demand in the MRIO model, and therefore their emissions are not allocated through the economic model and thus do not inherit economic uncertainties.

Contrary to the production perspective, the national consumption-based emissions are more dominated by metric uncertainties, due to different mix of pollutants. Disaggregation of the consumption emissions reveals that metric uncertainties usually dominate the sectors for the top emitters, and that uncertainties in economic data also usually increase more than the emission uncertainties at the sector level. For these nations, disaggregated sectoral emission uncertainties have a median value between 0.3 and 11 percentage points above the national aggregate, while the metric uncertainties have a median value between 2 and 8 percentage points above the national aggregated level, and economic uncertainty have an increase between 4 and 10 percentage points.

Figure 10 show GTP values and uncertainties for the same sectors and regions, for both territorial and consumption perspectives. Comparing the allocation differences due to different perspectives help explain the change in uncertainties when going from production to consumption. Agriculture and mining see the largest sectoral decrease in uncertainties due mainly to different mix of pollutants (increased CO_2), while transport and non-energy intensive manufacturing see an increase due to increased allocations of non-CO_2 emissions like SO_2. Similar differences can be seen for regions: India and Brazil are uncertain due to SO_2 and CH_4 emissions, while the US consists mostly of CO_2.

Most regions have quite similar uncertainty in both perspectives, indicating that the economic uncertainties do not play a major role for the large regions. The difference of uncertainties in the allocation perspectives can mainly be attributed to: (1) different mix of pollutants and (2) different allocations of emissions to sectors. The first effect gives net emission importers higher uncertainty in some sectors, due to highly uncertain pollutants (e.g. the share of non-CO_2 emissions in the UK is 30 % higher using consumption-based emissions, assuming absolute values), while other sectors decrease uncertainties due to the increased allocation of CO_2. The second effect is introduced when aggregating sectors to national level. The production emissions in a region are often dominated by a few large sectors, while the consumption-based emissions are distributed more evenly among the same sectors. This difference in distribution cause different relative errors on the aggregated result, even tough the sectoral uncertainties and the sum of emissions might be the same. Thus, on the national level, this effect creates smaller uncertainties. The combined results may give consumption-based emissions less uncertainty than production emissions on the national level (usually within 1–2 % for the top emitters).

In the Supplement we demonstrate how to calculate consumption uncertainty analytically for a simple one-sector, two-region world economy. This reveals that the consumption uncertainty can be lower, under conditions that are not unusual. How this analytical solution generalizes to larger systems requires further research. A similar finding was also found by Peters et al. (2012).

The AGTP emissions include uncertainties on CO_2, thus sectoral and regional uncertainties are larger and differences are reduced since it is the most common pollutant (Fig. 11). In this view, e.g. Chinese and US emissions overlap greatly within the given uncertainties, suggesting that the ordering is uncertain. The corresponding GTP values have less overlap. This may have large policy implications in terms of responsibility.

Other choices may also change the relative importance and uncertainty of regions and sectors. Choosing 20 years as time horizon would give lower relative uncertainties for all pollutants because of lower uncertainties for lifetime and climate sensitivity, except for SO_2, BC, OC and NH_3 due to their short-lived nature, thus regions and sectors with large emissions or consumption of SLCFs will be given larger uncertainties. Choosing 100 years will in most cases give higher relative uncertainties and give SLCFs less importance (see Fig. 7). Overall, we find the uncertainties to be highly sensitive to methods and choices.

4 Discussion

This study investigates parametric uncertainties in the temperature response to territorial- and consumption-based emissions with uncertainty contributions from economic data, emissions data and metric parameters. Structural uncertainties (dataset and model differences) and other contributing factors such as emission metric, attribution methods and indicators of climate change may be equally important when assessing uncertainties, but we did not investigate those here (den Elzen et al., 2005; Höhne et al., 2011; Peters et al., 2012). Earlier studies have shown relatively low uncertainties when estimating countries' contributions to climate change. Prather et al. (2009) estimated an uncertainty range of −27 to +32 % for the global warming caused by Annex I countries for the period 1990–2002 (0.11 ± 0.03 °C using 16–84 % confidence interval). Similar to them, we find that climate modeling generally has the largest contribution to total uncertainty on an aggregated level.

Very few studies have looked at uncertainties in consumption-based emissions inventories. Lenzen et al. (2010) found lower uncertainties for the UK carbon footprint (relative standard deviation of 5 % in 2001) than our results (±9 %), but is this probably because we include other pollutants and metric uncertainties. Other studies have indicated, similar to this, that the uncertainties in consumption-based emissions mostly come from the emission datasets and not from the economic data (Wilting, 2012; Andrew and Peters, 2013; Peters et al., 2012).

Our analysis has shown that uncertainties change depending on the (1) allocation perspective, (2) pollutants included, (3) metric and (4) aggregation. These changes in uncertainties may have implications for future mitigation policies.

1. First, we found little difference in the uncertainties in production- and consumption-based emissions. It is often assumed that consumption-based emissions are more uncertain (Peters, 2008), but parametric uncertainty analysis shows that the uncertainties are small; structural uncertainties may be larger (Peters et al., 2012). It is difficult to gauge how robust the parametric consumption-based emission uncertainties are. On the one hand, our chosen input uncertainties may be underestimated but there exists scant data to verify this. Increasing the uncertainties requires the need to rebalance the MRIO tables used in the analysis, which may introduce correlations and additional uncertainties resulting from the balancing process. Due to the computationally expensive nature of this type of analysis, further work would be required to assess the implications of rebalancing for each perturbation. On the other hand, the small uncertainties may reflect a realistic cancelling of numerous random errors (Lenzen et al., 2010). Settling these issues is a topic of future research.

2. Including SLCFs creates larger differences between regions' and sectors' uncertainties, where e.g. emissions from Brazil and India are much more uncertain than those of the other top 10 emitters due to large emissions in agriculture. Sectors such as agriculture, electricity and manufacturing have large non-CO_2 emissions, causing larger cooling and warming effects and additional uncertainties. It is often discussed that a shorter time horizon (e.g. 20 years) places more emphasis on the short-lived pollutants relative to CO_2, while with a longer time horizon (e.g. 100 years) the warming from CO_2 dominates. There is also a similar trade off with uncertainty: in the short term, the uncertainties are much larger due to the SLCFs,

and thus the temperature effect of policies to reduce SLCFs have more uncertain outcome; in the long-term, the more certain temperature effects of CO_2 dominate and the uncertainty due to the SLCFs becomes less relevant. Thus, uncertainty may tend to favor a more certain outcome on CO_2 mitigation compared to SLCFs. This hypothesis would require deeper analysis using economic and other models that incorporate uncertainty into decision making.

3. The GTP values have much smaller uncertainties than the AGTP metric, due to (1) the dominance of CO_2 which has $GTP_{CO_2} = 1$ and no uncertainty by definition and (2) the scaling by $AGTP_{CO_2}$ in the denominator which effectively reduces the impact of climate-sensitivity uncertainty in the GTP. This suggests that a normalized metric, GTP, may be better than an absolute metric, AGTP, in terms of uncertainties. In perspective, the underlying uncertainties are ultimately the same, but they have just been shifted to different variables and scaled out. Thus, a GTP focus may give the impression of greater uncertainty in CO_2. Other metrics, like the GWP, have lower uncertainties then the GTP as they do not include the response of the climate system (Olivié and Peters, 2013). Despite the metric uncertainties, it is unclear what role they should play in policy. From a scientific point of view the uncertainties are important, but in policy, once a metric and its parameters are chosen, their uncertainties are likely to be disregarded in subsequent analysis. This is an area that needs further consideration.

4. Aggregation changes the importance of the uncertainty contribution between the different components (economic data, emissions data and metric), as only the emissions data uncertainty have been estimated at both sector and regional level, while they all are affected by reduction in uncertainties by aggregation. On the global sectoral level, uncertainties are dominated by metrics. For the regions, emissions uncertainties often dominate over emission uncertainties. At the sector level, much larger variations are seen, with even economic uncertainties

dominating in very small sectors. Thus, the role of uncertainties may differ depending on the level of aggregation.

These results presented are broadly in line with the existing literature on this topic (Wilting, 2012; Fuglestvedt et al., 2010; Joos et al., 2013; Lenzen et al., 2010; Myhre et al., 2013b; Olivié and Peters, 2013). However, our results are limited by the quality of the uncertainty information available as input into our analysis. Despite the widespread usage of the input data in a wide variety of studies, there still exists virtually no uncertainty information on economic data, and limited data on the uncertainties in emission statistics and metric parameters.

5 Conclusions

We analyzed emissions from 129 countries and 58 sectors with 31 SLCFs and GHGs when estimating countries' territorial and consumption-based emissions for 2007. We use top-down uncertainty estimates to derive sector level uncertainties, and use these to perturb the economic data, emissions data and metric parameters in a Monte-Carlo model. We find the results are sensitive to some parameters (such as the uncertainty of the climate response and the datasets) and assumptions (such as developing countries are assigned twice the uncertainty for emissions and economic data), but especially to choices regarding allocation perspective, pollutants included, metric used and aggregation level of the results.

We find only minor uncertainty differences between allocation perspectives (production vs. consumption) for the top regions, and uncertainties in the economic data are very small for the large countries. Since economic data generally does not have uncertainty information, it was necessary to estimate the uncertainties of the economic data and there is little data to verify our estimates. At the sectoral level, larger differences between production and consumption are found. The inclusion of SLCFs increases both the emissions and metric uncertainties, and gives larger variations between regions and sectors. A different choice of time horizon would change the prioritization of

the gases and corresponding uncertainties. At the global level, the metric uncertainty (which is dominated by climate sensitivity) dominates over emission and economic uncertainty. At the regional level, the uncertainties from emissions are more important.

Our work points to key areas of future research required to reduce uncertainties. The climate sensitivity generally dominates uncertainties, and this is where the largest improvements can potentially be made. Most climate sensitivity literature focuses on the long-term sensitivity, whereas for metrics (and undoubtedly most mitigation analysis), the temporal path to the equilibrium response is most relevant (impulse response function). Thus, we suggest much deeper analysis is needed on the time-evolution of the temperature response. Emission statistics are routinely collected, but generally have poorly defined uncertainties. Our work indicates that large improvements in the reporting and analysis of emission uncertainties are needed. Additional metric uncertainties can be improved through a better characterization of metric parameters (radiative efficiencies and lifetimes). Reducing uncertainties in metrics and emission statistics will reduce both uncertainties in production- and consumption-based emissions. The uncertainty in the economic data was necessarily based on crude assumptions. While we found that the economic uncertainties were small, this result needs to be confirmed by more comprehensive analysis. This will have the effect of reducing uncertainties in consumption-based emissions only.

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Table 1. Global emissions and uncertainties. The uncertainties indicate the 5–95 % (90 %) percentile range. PFCs include: C2F6, C3F8, C4F10, C5F12, C6F14, C7F16, CF4, c-C4F8. HFCs include: HFC-125, HFC-134a, HFC-143a, HFC-152a, HFC-227ea, HFC-23, HFC-236fa, HFC-245fa, HFC-32, HFC-365mfc, HFC-43-10-mee, following UNEP (2012).

Pollutant	Global emissions (kt)	Uncertainty	Emissions references	Uncertainty references
PFCs	$1.47 \times 10^{+1}$	±17 %	European Commission (2011)	UNEP (2012)
CH_4	$3.25 \times 10^{+5}$	±21 %	European Commission (2011)	UNEP (2012)
CO	$9.47 \times 10^{+5}$	±25 %	European Commission (2011)	European Commission (2011)
CO_2	$3.14 \times 10^{+7}$	±8 %	European Commission (2011)	UNEP (2012)
HFCs	$2.68 \times 10^{+2}$	±17 %	European Commission (2011)	UNEP (2012)
N_2O	$1.02 \times 10^{+4}$	±25 %	European Commission (2011)	UNEP (2012)
NF_3	$1.58 \times 10^{+1}$	±26 %	European Commission (2011)	Weiss et al. (2008)
NH_3	$4.92 \times 10^{+4}$	±25 %	European Commission (2011)	Clarisse et al. (2009)
NMVOC	$1.60 \times 10^{+5}$	±50 %	European Commission (2011)	European Commission (2011)
NO_x	$1.27 \times 10^{+5}$	±25 %	European Commission (2011)	European Commission (2011)
SF_6	$6.17 \times 10^{+0}$	±10 %	European Commission (2011)	Levin et al. (2010)
SO_2	$1.22 \times 10^{+5}$	±11 %	European Commission (2011)	Smith et al. (2010)
BC	$5.22 \times 10^{+3}$	±84 %	Shindell et al. (2012)	Bond et al. (2004)
OC	$1.34 \times 10^{+4}$	±84 %	Shindell et al. (2012)	Bond et al. (2004)

Table 2. Example of perturbations of sectors for a single region r, and the resulting distribution on the national total. This bottom-up uncertainty estimate may not be consistent with top-down uncertainty estimates.

Region r	Sector 1	Sector 2	Sector 3	Sector n	National total (sum of sectors)	Distribution on national totals
Perturbation 1	x_{11}	x_{12}	x_{13}	x_{1n}	X_1	
Perturbation 2	x_{21}	x_{22}	x_{23}	x_{2n}	X_2	$\rightarrow X_N$
Perturbation 3	x_{31}	x_{32}	x_{33}	x_{3n}	X_3	
Perturbation i	x_{i1}	x_{i2}	x_{i3}	x_{in}	X_i	

Table 3. Metric parameters with uncertainties. Note that the uncertainties are derived from CMIP5 data and Joos et al. (2013), but we use the corresponding distributions listed in Tables 5 and 6 in the study by Olivié and Peters (2013) to account for correlations.

Parameters	Values	Unit	Uncertainties
Climate sensitivity f_1	0.43	$K\,(W\,m^2)^{-1}$	±29 %
Climate sensitivity f_2	0.32		±59 %
Climate sensitivity decay τ_1	2.57	year	±46 %
Climate sensitivity decay τ_2	82.24		±192 %
CO_2 weight a	0.23		±20 %
CO_2 weight a_1	0.28		±33 %
CO_2 weight a_2	0.35		±28 %
CO_2 weight a_3	0.14		±30 %
CO_2 decay τ_0	INF	year	–
CO_2 decay τ_1	239.6		±58 %
CO_2 decay τ_2	18.42		±68 %
CO_2 decay τ_3	1.64		±63 %

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Table 4. RF values and uncertainties. Note that CO, NMVOC and NO_x are precursors, which have an effect on O_3 and CH_4 concentrations. Because of this, no single RF value can be given. The uncertainties indicate the 5–95 % (90 %) percentile range. Parameters from IPCC (2007) are taken from Table 2.14, p. 212–213.

Pollutant	RF ($W m^{-2} kg^{-1}$)	Uncertainty	RF references	Uncertainty references
PFCs	6.40×10^{-12}–1.06×10^{-11}	±10 %	IPCC (2007)	Myhre et al. (2013a)
CH_4	1.82×10^{-13}	±17 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
CO	–	±24 %	Derwent et al. (2001)	Myhre et al. (2013a)
CO_2	1.81×10^{-15}	±10 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
HFCs	6.74×10^{-12}–1.53×10^{-11}	±10 %	Fuglestvedt et al. (2010), IPCC (2007)	Myhre et al. (2013a)
N_2O	3.88×10^{-13}	±17 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
NF_3	1.66×10^{-11}	±10 %	IPCC (2007)	Assumed
NH_3	-1.03×10^{-10}	±123 %	Shindell et al. (2009)	Myhre et al. (2013a)
NMVOC	–	±41 %	Collins et al. (2002)	Myhre et al. (2013a)
NO_x	–	±120 %	Wild et al. (2001)	Myhre et al. (2013a)
SF_6	2.00×10^{-11}	±10 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
Sulphate	-3.20×10^{-10}	±50 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
BC	1.96×10^{-09}	±66 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
OC	-2.90×10^{-10}	±68 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)

Table 5. Lifetimes and uncertainties. The uncertainty on lifetime for several gases are assumed, but a sensitivity analysis revealed that a change of this uncertainty will not have a large impact on the results (see Sect. 3.3). Note that CO, NMVOC and NO_x are precursors, which have an effect on O_3 and CH_4 concentrations. Because of this, no single RF value can be given. Values and uncertainties for CO_2 is given in Table 3. The uncertainties indicate the 5–95 % (90 %) percentile range. Parameters from IPCC (2007) are taken from Table 2.14, p. 212–213.

Pollutant	Lifetime (years)	Uncertainty	Lifetime references	Uncertainty references
PFCs	2600–50000	±20 %	Fuglestvedt et al. (2010)	Assumed
CH_4	12	±19 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
CO	–	±20 %	Fuglestvedt et al. (2010)	Assumed
CO_2	–	–	Fuglestvedt et al. (2010)	–
HFCs	1.4–270	[±12–±29 %]	Fuglestvedt et al. (2010), IPCC (2007)	Myhre et al. (2013a), SPARC (2013)
N_2O	114	±13 %	Fuglestvedt et al. (2010)	Myhre et al. (2013a)
NF_3	740	±13 %	Fuglestvedt et al. (2010)	SPARC (2013)
NH_3	0.02	±20 %	Fuglestvedt et al. (2010)	Assumed
NMVOC	–	±20 %	Fuglestvedt et al. (2010)	Assumed
NO_x	–	±20 %	Fuglestvedt et al. (2010)	Assumed
SF_6	3200	±20 %	Fuglestvedt et al. (2010)	Assumed
Sulphate	0.01	±20 %	Fuglestvedt et al. (2010)	Assumed
BC	0.02	±20 %	Fuglestvedt et al. (2010)	Assumed
OC	0.02	±20 %	Fuglestvedt et al. (2010)	Assumed

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Table 6. Uncertainties in allocated emissions due to uncertainties in the economic dataset, by top 10 emitters. The territorial emissions are not perturbed, thus they have no uncertainty.

		Region	Territorial	Exports	Uncertainty	Imports	Uncertainty	Consumption	Uncertainty
Top 10 emitters globall	1	China	7269	1966	1.7 %	400	2.1 %	5703	0.7 %
	2	United States of America	6380	744	1.1 %	1411	1.2 %	7047	0.3 %
	3	Russian Federation	2027	600	1.0 %	216	1.3 %	1642	0.5 %
	4	India	1812	232	2.0 %	186	2.6 %	1766	0.5 %
	5	Japan	1381	257	1.3 %	471	1.4 %	1595	0.5 %
	6	Germany	957	324	0.9 %	498	1.0 %	1130	0.6 %
	7	Brazil	750	127	2.1 %	116	3.1 %	739	0.7 %
	8	Canada	626	194	1.0 %	209	1.5 %	641	0.7 %
	9	UK	616	134	1.0 %	410	1.1 %	892	0.6 %
	10	Korea	547	158	1.9 %	214	2.4 %	602	1.2 %

Table 7. Metric values uncertainties for 20, 50 and 100 years time horizon. All metric parameters (excluding emissions) were perturbed. The uncertainties indicate the 5–95 % (90 %) percentile range, where the plus-minus notation is half of the 90 % CI. Numbers are rounded to nearest 5 %, as multiple MC runs would give slightly different results (usually within 1–2 %).

Pollutants	AGTP20	AGTP50	AGTP100	GTP20	GTP50	GTP100
PFCs	±30 %	±35 %	±35 %	±20 %	±20 %	±20 %
CH_4	±45 %	±70 %	±75 %	±35 %	±55 %	±70 %
CO	±45 %	±65 %	±75 %	±35 %	±45 %	±65 %
CO_2	±35 %	±40 %	±40 %	±0 %	±0 %	±0 %
HFCs	±30 %	±40 %	±40 %	±20 %	±20 %	±20 %
N_2O	±35 %	±40 %	±40 %	±25 %	±25 %	±30 %
NF_3	±35 %	±35 %	±35 %	±20 %	±25 %	±25 %
NH_3	±180 %	±165 %	±170 %	±165 %	±150 %	±165 %
NMVOC	±50 %	±65 %	±75 %	±35 %	±45 %	±65 %
NO_x	±35 %	±65 %	±95 %	±35 %	±50 %	±80 %
SF_6	±35 %	±35 %	±35 %	±20 %	±20 %	±25 %
SO_2	±110 %	±95 %	±100 %	±100 %	±80 %	±100 %
BC	±125 %	±110 %	±110 %	±110 %	±95 %	±110 %
OC	±125 %	±110 %	±115 %	±110 %	±95 %	±110 %

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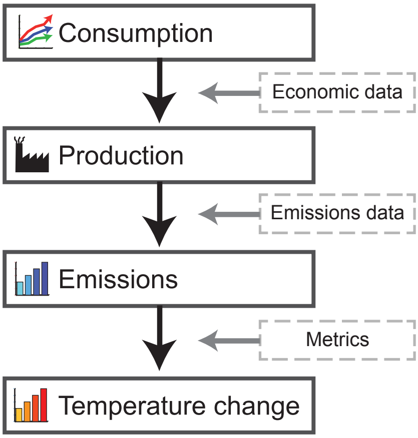

Figure 1. Flow chart of activities (bold boxes) and the datasets that determine transitions between them (dashed boxes).

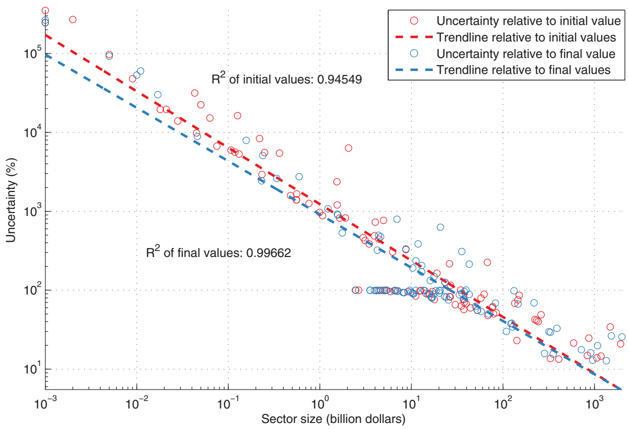

Figure 2. Error distribution of selected GTAP input-output data, and trendlines showing the fit of the general functional relationship explained by Eq. (1).

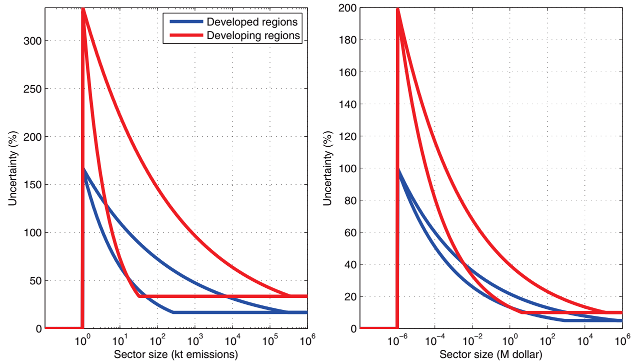

Figure 3. Functional relationship between sector sizes on horizontal axis (in kt CO_2 emissions and million US dollars, respectively) and relative uncertainty on vertical axis. The red lines outline the range of developing regions, while the blue lines show the range of developed countries. The form of this relationship is established indiependently for each pollutant.

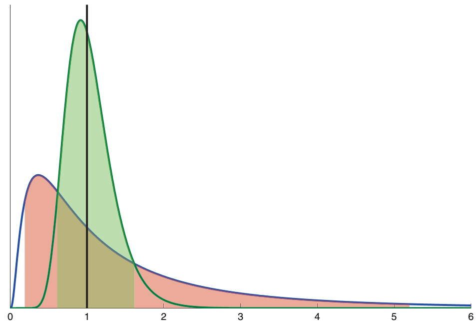

Figure 4. Distributions depending on median values and uncertainty. Both distributions have a median = 1, while the near-normal distribution (green) has a relative uncertainty of 100 %, the skew distribution has a relative uncertainty of 500 %. The green and red shaded areas indicate the 5–95 % (90 %) confidence intervals.

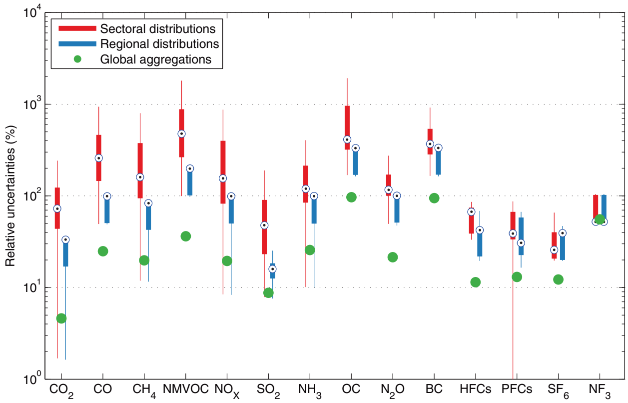

Figure 5. Relative uncertainties (90 % CI) of all pollutants for all sectors (red boxplots), for national aggregates (blue boxplots) and global aggregates (green dots). The edges of the boxes indicate the 25th and 75th percentile, and the whiskers include extreme data points, but not outliers. The blue target symbol indicates the median value of the distributions. Pollutants are sorted according to global emissions in tonnes.

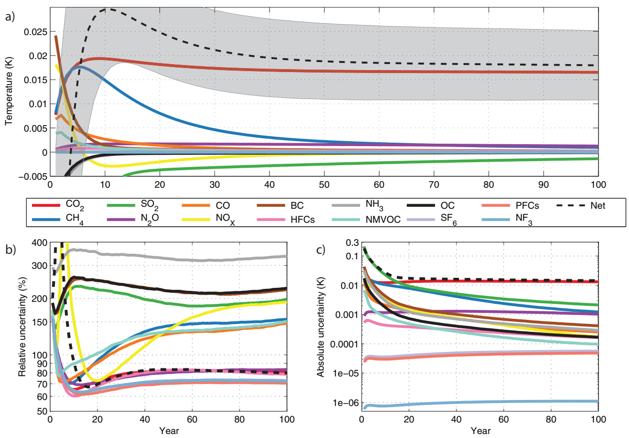

Figure 6. (a) The AGTP for a range of pollutants, with **(b)** relative and **(c)** absolute uncertainties due to metric parameters. Pollutants are sorted in the legend according to absolute temperature impact at 50 years. The box inside subplot **(a)** shows the same figure on a different scale, and the shaded area around the net effect indicate the 90 % CI uncertainty. Subplot **(b)** has a log scale, showing relative uncertainties. Subplot **(c)** (also using log scale) shows the absolute uncertainty for a 90 % CI, of which half is the upper shaded area in **(a)** and the other half is the lower shaded area.

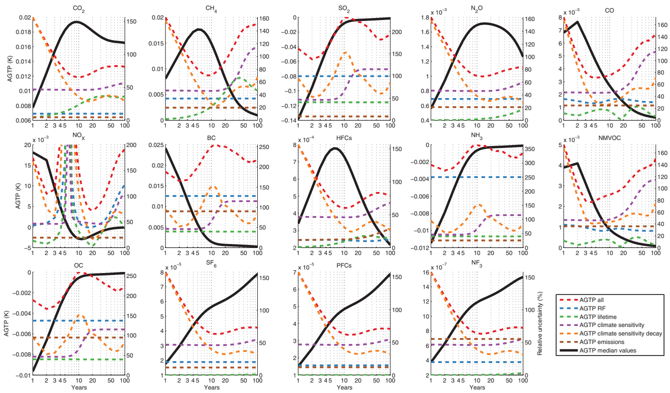

Figure 7. AGTP values (black lines) for all pollutants (sorted by absolute temperature impact at 50 years time horizon) and relative uncertainties (dashed lines) for metric parameters, on the right vertical axis. *AGTP median values* use parameters from the literature, while *AGTP all* show uncertainty with all parameters perturbed (excluding emissions). Uncertainties indicate the 90 % CI range of the median values. Global emission uncertainties are derived from sector aggregations, and are the same as showed in Fig. 5.

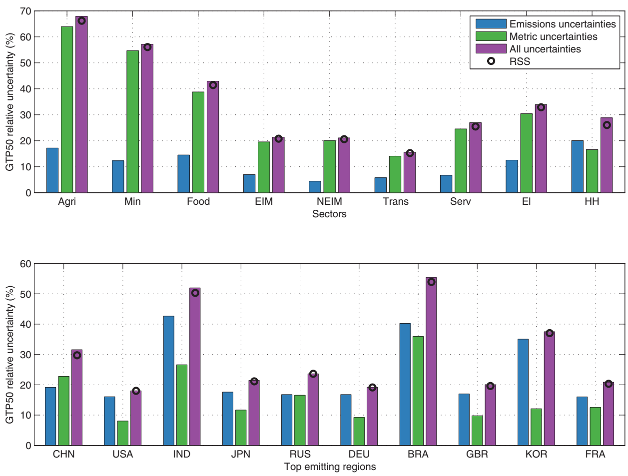

Figure 8. Territorial perspective of emissions and metric uncertainty using GTP50. Top graph shows global emissions in sectors they occur in, while bottom graph shows regional emissions. Each of the components is represented by an individual MC. The black circle indicates the aggregated RSS uncertainty. The uncertainty represents the 5–95 % CI.

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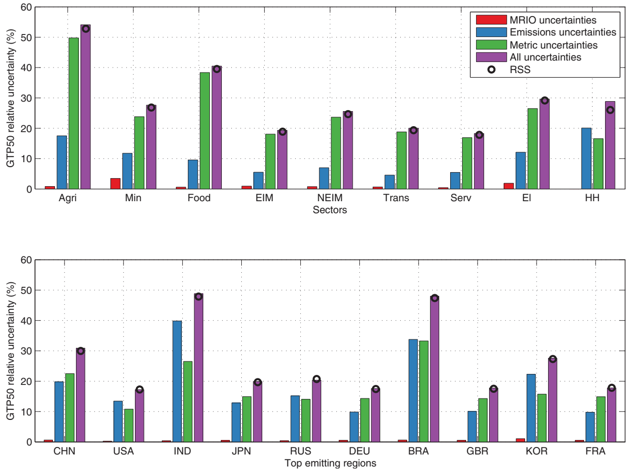

Figure 9. Consumption perspective of emissions, metric and MRIO uncertainty using GTP50. Top graph shows global emissions going to sectors, while bottom graph shows regional consumption.

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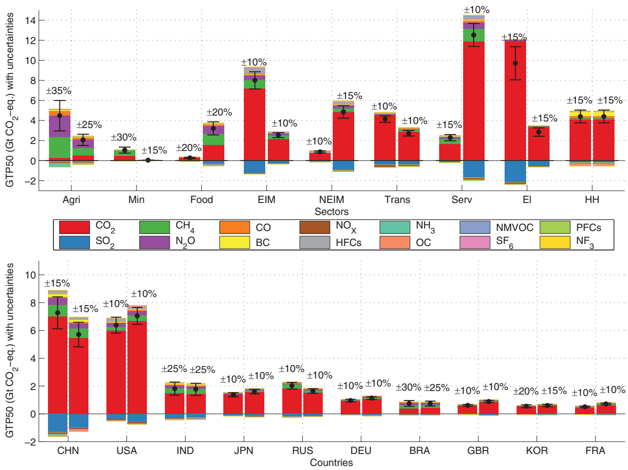

Figure 10. GTP values and uncertainties for territorial (first bars) and consumption (second bars) perspectives. Percentages on top of the bars indicate total uncertainty (rounded to closest 5 %).

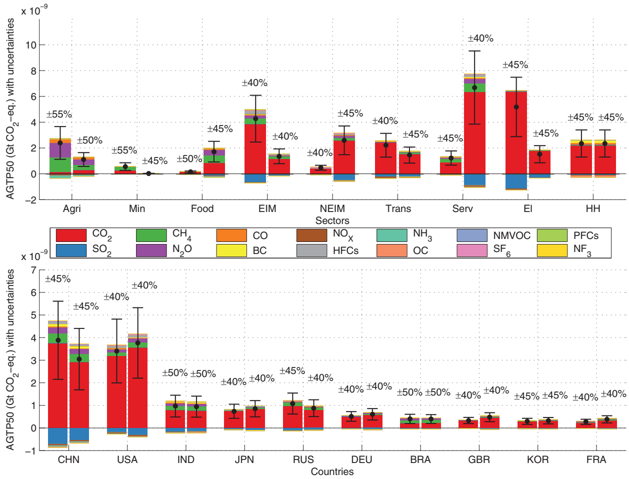

Figure 11. AGTP values and uncertainties for territorial (first bars) and consumption (second bars) perspectives. The uncertainty reflects a combination of all pollutants including CO_2. Percentages on top of the bars indicate total uncertainty (rounded to closest 5 %).

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Uncertainty in temperature response of current consumption-based emissions estimates

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Supplementary material

Analytical solution of consumption uncertainty for a one-sector, two-region

Here we present a simple analysis of the conditions under which a region's consumption uncertainty will be lower than its production uncertainty by virtue of uncertainty mixing through the MRIO model.

$$\begin{pmatrix} q_1 & q_2 \end{pmatrix} = \begin{pmatrix} \frac{F_1}{x_1} & \frac{F_2}{x_2} \end{pmatrix} \begin{pmatrix} L_{11} & L_{12} \\ L_{21} & L_{22} \end{pmatrix} \begin{pmatrix} y_1 & 0 \\ 0 & y_2 \end{pmatrix}$$

$$q_1 = y_1 \left(\frac{L_{11}}{x_1} F_1 + \frac{L_{21}}{x_2} F_2 \right)$$

$$\Delta q_1 = y_1 \sqrt{ \left(\frac{L_{11}}{x_1} \Delta F_1 \right)^2 + \left(\frac{L_{21}}{x_2} \Delta F_2 \right)^2 }$$

$$a_1 = \frac{L_{11}}{x_1}, a_2 = \frac{L_{21}}{x_2}$$

$$\frac{\Delta q_1}{q_1} = \frac{\sqrt{(a_1 \Delta F_1)^2 + (a_2 \Delta F_2)^2}}{a_1 F_1 + a_2 F_2}$$

$$\frac{\Delta q_1}{\Delta F_1} \Big/ \frac{q_1}{F_1} = \frac{\frac{1}{\Delta F_1} \sqrt{(a_1 \Delta F_1)^2 + (a_2 \Delta F_2)^2}}{\frac{1}{F_1} (a_1 F_1 + a_2 F_2)}$$

$$= \frac{\sqrt{a_1{}^2 + \left(a_2 \frac{\Delta F_2}{\Delta F_1} \right)^2}}{a_1 + a_2 \frac{F_2}{F_1}}$$

$$= \frac{\sqrt{1 + \left(\frac{a_2}{a_1} \frac{\Delta F_2}{\Delta F_1} \right)^2}}{1 + \frac{a_2}{a_1} \frac{F_2}{F_1}}$$

$$\left(\frac{\Delta q_1}{\Delta F_1} \Big/ \frac{q_1}{F_1} \right)^2 = \frac{1 + \left(\frac{a_2}{a_1} \frac{\Delta F_2}{\Delta F_1} \right)^2}{1 + \left(\frac{a_2}{a_1} \frac{F_2}{F_1} \right)^2 + 2 \frac{a_2}{a_1} \frac{F_2}{F_1}}$$

$$r_1 = \frac{\Delta F_1}{F_1}, r_2 = \frac{\Delta F_2}{F_2}$$

$$\frac{\Delta q_1 \quad q_1}{\Delta F_1 \quad F_1}^{2} = \frac{1 + \quad \frac{r_2}{r_1}^{2} \quad \frac{a_2}{a_1}\frac{F_2}{F_1}^{2}}{1 + \quad \frac{a_2}{a_1}\frac{F_2}{F_1}^{2} + 2 \quad \frac{a_2}{a_1}\frac{F_2}{F_1}^{2} \quad \frac{a_2}{a_1}\frac{F_2}{F_1}}$$

$$= \frac{1 + \quad \frac{r_2}{r_1}^{2} \quad \frac{a_2}{a_1}\frac{F_2}{F_1}^{2}}{1 + \quad 1 + \frac{2}{\frac{a_2 F_2}{a_1 F_1}} \quad \frac{a_2}{a_1}\frac{F_2}{F_1}^{2}}$$

Therefore,

$$\frac{\Delta q_1 \quad q_1}{\Delta F_1 \quad F_1} < 1$$

if and only if

$$\frac{\Delta F_2 \quad F_2}{\Delta F_1 \quad F_1}^{2} < 1 + 2\frac{L_{11}}{L_{21}}\frac{F_1}{F_2}\frac{x_1}{x_2}$$

$$\frac{\Delta F_2}{F_2} < \frac{\Delta F_1}{F_1} \quad \overline{1 + 2\frac{L_{11}}{L_{21}}\frac{F_1}{F_2}\frac{x_1}{x_2}}$$

Since the radical term is always ≥ 1, we can say that (at least) if $\frac{\Delta F_2}{F_2} < \frac{\Delta F_1}{F_1}$ then $\Delta q_1 \quad q_1 < \Delta F_1 \quad F_1$. In this simple case, we can simply say that region 1's production uncertainty is diluted by region 2's lower uncertainty to give a lower consumption uncertainty for region 1. This would be expected. However, we can also say from the analysis that there are conditions under which, even though the relative uncertainty of region 2 is larger than that of region 1, the consumption uncertainty of region 1 is still lowered by virtue of imports from region 2. Generalisation of this result to larger systems is left for future work.

Table S1: Sector aggregations, from GTAP sectors to 9 sector aggregation.

Agriculture	Paddy rice Wheat Cereal grains not elsewhere classified Vegetables, fruit, nuts Oil seeds Sugar cane, sugar beet Plant-based fibers Crops not elsewhere classified Cattle, sheep, goats, horses Animal products not elsewhere classified Raw milk Wool, silk-worm cocoons Forestry

	Fishing
Mining	Coal Crude Oil Gas Minerals not elsewhere classified
Food	Meat: cattle, sheep, goats, horse Meat products not elsewhere classified Vegetable oils and fats Dairy products Processed rice Sugar Food products not elsewhere classified Beverages and tobacco products
Energy-intensive manufacturing	Paper products, publishing Refined petroleum Chemicals, rubber, plastic products Non-metallic minerals Ferrous metals Non-ferrous metals
Non energy-intensive manufacturing	Textiles Wearing apparel Leather products Wood products Metal products Motor vehicles and parts Transport equipment not elsewhere classified Electronic equipment Machinery and equipment Manufactures not elsewhere classified
Transport	Transport not elsewhere classified Sea transport Air transport
Services	Gas manufacture, distribution Water Construction Trade Communication Financial services not elsewhere classified Insurance Business services not elsewhere classified Recreation and other services Public Administration/Defence/Health/Education Dwellings
Electricity	Electricity
Households	Households